Influencing Health Decisions using Robot Counseling, Mobility, and Gesture

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ABSTRACT

Mobile humanoid robots have the ability to move to a user's location and engage them in persuasive multi-modal dialog to promote health behavior change. We conducted a randomized two-factor experiment to evaluate the effect of having a robot use mobility and nonverbal behavior (deictic pointing gestures) without speech on influencing user food choices. We also evaluated whether trust-building dialog with the robot impacted food choice persuasion as a second, independent factor. In a study with 23 participants, we found that robot pointing at healthy foods did lead to better dietary choices and that trust-building dialog led to increased self-reported trust in the robot. However, there were no effects of trust on persuasion or other interaction effects of the two factors.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

Persuasion, Health Behavior Change, Trust, Working Alliance, Cuing, Gesture

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Figure 1: In this study, we evaluate how nonverbal gestures and trust building can influence dietary health decisions.

1 INTRODUCTION

Health behavior such as poor diet, physical inactivity, and tobacco use are the leading risk factors for disability in the US, and poor diet alone is associated with 26% of deaths [30]. Helping individuals change their health behavior is a complex undertaking that has spawned entire disciplines and industries.

Although much of behavioral medicine is oriented to changing health attitudes and habits through passive messaging or episodic counseling [15], interventions that can provide information and motivation at the time and place a person is making a health decision arguably have the greatest opportunity for impact. Mobile humanoid robots may be ideal for performing in this role, given their ability to move to a person's location, counsel them on their decision, and use nonverbal behavior–such as hand gesture–to inform and influence. Several studies to date have evaluated humanoid robots in the role of health coach or counselor [42] [24], and a few have evaluated the use of hand and arm gestures in demonstrating exercise [10]. However, the use of mobility and gesture to cue health-relevant objects in the user's environment remains a relatively unexplored area of investigation.

In this work, we explore the use of mobility and deictic (pointing) gestures by a humanoid robot to indicate health-relevant objects in a person's environment at the time and place they are making a health decision. Providing such in-context reminders–referred to as "stimulus control" in the transtheoretical model of health behavior change [31]–are among the most powerful techniques for changing behavior. In order to motivate the robot's behavior, and establish trust and therapeutic alliance with individuals prior to health decision events, we also explore the use of health counseling by a robot in conjunction with its cuing behavior. Therapeutic alliance is the trust and belief that a helper and helpee have in each other as team-members in achieving a desired outcome, and has been shown to be an important determiner of outcomes in all areas of helping, including health counseling and therapy [21].

Our test domain is nutrition: helping individuals maintain healthy diets. Food choice is one of the most important health decisions people make on a regular basis, and poor diet quality is one of the top leading risk factors for death and disability in the US [30]. Fruit and vegetable consumption alone plays a protective role in a large number of cancers, and is associated with reduced risk for heart

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disease, stroke, and hypertension, yet only one in ten US adults meet dietary guidelines [28]. Similar arguments can be made for dietary fiber [1], consumption of sugar-free beverages [29], and several other aspects of diet.

1.1 Theoretical Framework

While we are ultimately interested in long-term health behavior change [31], we position our current study within the literature on social influence and persuasion [6] [37]. The persuasiveness of a message may be affected by the credibility of the source and by the interpersonal relationship between source and recipient. Credibility has further been shown to depend on assessments of the source's trustworthiness and expertise. The relationship between source and recipient need not be extensive or long-lasting to influence persuasion. For example, Burger et. al. showed that participants were more likely to comply with a request from a confederate they had interacted with previously, even if the previous interaction consisted solely of sitting quietly in a room together for a short period of time [4]. Howard showed that asking someone how they were feeling, and acknowledging the response, led to greater compliance with a charitable request [23].

1.2 Virtual Cafeteria Testbed

To explore our research questions in a context in which multiple health decisions are made by a person in a short time span, we constructed a "virtual cafeteria" (Figure 1), similar in concept to those used by Ung, et al. [38]. These are physical simulations of environments, such as cafeterias or pantries, stocked with fake food of varying nutritional quality, in which study participants can make food selections in order to evaluate the impact of different interventions on food choice.

In our virtual cafeteria, participants are asked to assemble a number of lunches for others by selecting prepared food items from a pantry. While they are making lunches, a mobile humanoid robot can move within the cafeteria to counsel participants verbally or point at food items in the pantry ("cuing"). In our initial experiment we are primarily interested in determining the influence of these cuing behaviors on compliance (whether a participant followed the robot's recommendation) and the overall dietary quality of the lunches they assemble, given that the robot always recommends healthy food options. We are also interested in exploring whether an initial diet counseling conversation with the robot affects participant trust and therapeutic alliance attitudes towards the robot, and whether this initial counseling increases overall compliance with cuing and the dietary quality of the assembled lunches.

1.3 Hypotheses

Given our theoretical frameworks for social influence and persuasion, we hypothesize that:

H1: The robot's pointing at healthy food options at the time and place a person is deciding among multiple choices ("cuing") will lead to healthier meals, as measured by the Healthy Eating Index (HEI, a standard measure of diet quality).

H2: An initial diet counseling conversation with the robot will lead to greater feelings of trust and therapeutic alliance which, in turn, will boost overall compliance with cuing and healthier meals, as measured by HEI.

2 RELATED WORK

There is now a large body of literature on persuasive computing in general [11] and persuasive robotics [36] in particular.

2.1 Persuasive robots

Persuasive robotics requires an understanding of how persuasion in human-human interactions translates to human-robot interactions [3].

Leveraging the Elaboration Likelihood Model, an established model of persuasion in human-human interaction, Winkle et al. [43] evaluated the strategies of goodwill, similarity, and credibility on health behavior compliance, in having participants perform a simple wrist rotation exercise.

Ham, et al., evaluated robot persuasion to improve attitudes towards energy conservation, finding that social feedback is better than factual feedback, and that negative feedback is better than positive feedback for persuading behavior change [16][17].

Rincon, et al. [33] designed a social robot *EmIR* for assisting older adults in their daily activities. The robot uses three strategies of argumentation (analogy, popular practice, and expert opinion) to persuade users to accept suggestions of activities and events. The persuasion techniques implemented were based on the persuasion architecture designed by Costa et al. [7] which provides a framework for using persuasion to provide recommendations that fit the user's profile and interests.

Herse, et al. [20] explored how different embodiment types influence persuasion in recommendation systems. Through a vignette study, they compared persuasion across two recommendation statements (one related to the atmosphere and one about the staff) and three hypothetical embodiment types (human, robot, information kiosk) which aimed to persuade the participants to choose one of two restaurant options.

Ghazali et al. [13] demonstrated that apparent gender congruence between user and robot may lead to persuasion, but not necessarily improve the trust between them. On the other hand, Siegel and Breazeal [36] showed that male users were more likely to donate money to a female robot compared to a male robot, while women demonstrated no preference. They also demonstrated that participants found robots of the opposite sex more credible, trustworthy, and engaging.

Hashemian et al. [19] explored social power and persuasion in HRI. Two humanoid robots that each employed a different social power strategy (one used a reward strategy and the other established itself as an expert on coffee) to encourage participants to pick between one of three different coffee packs. Both approaches were found to be equally persuasive. They also demonstrated that the relationship between social power and persuasion is not linear and that repeated persuasion attempts do not decay the perceived value of the rewards when rewards are used as the social power strategy. [18]

2.2 Robot Persuasion through Nonverbal Behavior

Persuasion has also been shown to be affected by an individual's use of nonverbal cues such as gaze and proximity [32].

Ju and Sirkin [25] explored the use of different mechanisms to attract the attention of people passing by a public kiosk. They found that the use of a waving robotic hand was better at persuading participants to engage with the kiosk compared to an animated hand on a display, demonstrating the enhanced persuasive ability of physicality in robots.

Ham, et al., demonstrated that persuasion was increased when a robot used a combination of both gazing and gesturing in a storytelling task [16].

Ghazali et al. [12] investigated the use of social cues as persuasion strategies. In a series of studies, they looked at how cues such as mimicry, praise, as well as emotional intonation, head movements, and facial expressions, can be used to persuade people to change their choices in trivial tasks. However, these studies relied on robot speech as the primary modality for persuasion, and did not investigate the persuasive effect of nonverbal behavior in isolation [12] [14].

Chidambaram et al. [5] explored how manipulations in the use of a robot's nonverbal cues (with and without the addition of speech cues) affected the participant's perceptions of the robot's persuasiveness and compliance with the robot's suggestions. Participants performed the *Desert Survival Task* [27] on a computer with a robot providing suggestions using a combination of verbal and nonverbal cues. The gestures used by the robot included pointing (deictic) gestures to reference itself and the participant, metaphorical gestures, to show a space containing an idea, and other kinds of gestures where appropriate. The study demonstrated that nonverbal signaling worked better than no signals and that nonverbal cues were effective only when combined with speech cues.

3 EXPERIMENTAL DESIGN

We constructed an experimental testbed comprised of a virtual cafeteria in which a participant assembles multiple meals, providing the opportunity for repeated trials experiments. We experimented with different strategies that a mobile humanoid robot in the cafeteria can use to persuade participant food selection choices.

In order to test our hypotheses, we designed an experiment with one between-participants factor, namely *ROBOT ROLE*; and one within-participants factor, namely *CUING*. Both of these factors had two conditions. The two conditions of *ROBOT ROLE* factor are *Counselor* and *Bystander*. For the experiments under *Counselor* condition, the robot is framed as a nutrition coach in a counseling session (§3.3) the participants went through with the robot prior to the experimental task (§3.1). During the experiments in the *Bystander* condition, the robot is introduced by the experimenter as an assistant that can help with food selections, but the robot does not talk directly to the participant. The two conditions of *CUING* factor are *Physical Cuing* and *No Cuing*. During the trials under *Physical Cuing* condition, the robot approaches the participant and the pantry to physically cue a healthy food item on the pantry shelves; and during the trials under *No Cuing* condition, the robot executes idle animations in its "home" position (Figure 1,2) and does not take any action. In these settings, the *Bystander* and *No Cuing* conditions serve as the control conditions for the experiment.

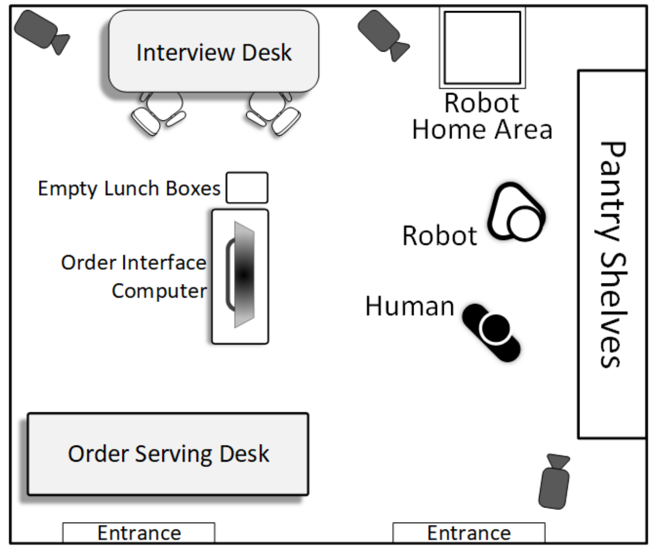

Figure 2: Laboratory layout used during the experiments.

3.1 Meal Assembly Task

In our experiments, we asked participants to assemble lunch boxes for 20 college students using the food items from the pantry located within the lab space and to place the assembled meals on a serving area. Meal orders are delivered to the participants through a touchscreen computer located within the lab space (Figure 2).

For each lunch box "trial", participants receive orders which are labeled either as "Specific Order" or "Chef's Choice!" (Figure 3). Specific Orders specify an exact set of food items and serve as training for the participants. Chef's Choice orders do not specify any food and leave the meal decision to the participant. These orders served as the experimental trials. For each experimental trial, participants are instructed to assemble a meal of at least 4 food items. Through the experiment, each participant completes 4 training trials, 8 *Physical Cuing* trials, and 8 *No Cuing* trials.

In every experiment, the first trial is a Specific Order, and the remaining 3 Specific Orders are randomized for each participant to be distributed within the following 9 trials. Additionally, the first Chef's Choice order received by each participant is set to be executed under *No Cuing* condition to prevent participants from building anticipation for the robot to assist them in the following trials. The remaining trials are randomized for each participant throughout the experiment.

The experiment sessions were video and audio recorded.

3.2 Virtual Cafeteria Pantry

In our virtual cafeteria, we created a pantry which contains 45 food items to assemble meals with. We used real food for long-shelf-life items and fake food for perishable items. Included food items were specifically selected to be the types that did not require any cooking (eg. salad, sandwich, chips) or that could be consumed by adding hot water or heating up (eg. ramen, pasta, soup). Participants are provided with a name tag under each item on the pantry shelves, but are not provided with any nutritional information about the items. Identical food items were clustered together and distributed throughout 4 racks which had 3 shelves each. There were 2 to 4 clusters of items on each of the 12 shelves.

Sixteen (16) of the food items on the pantry are categorized as being healthy choices in accordance with the nutritional indices provided in the Food and Nutrient Database for Dietary Studies (FNDDS,[39]) and Food Patterns Equivalents Database (FPED, [40]); and with the food quality scoring scheme provided by the Healthy Eating Index (HEI, [26]). These items are assigned to be randomly chosen for each *Physical Cuing* trial and cued to the participant by the robot. The healthy food items are distributed through the pantry so that there is at least one healthy option on each shelf. A complete list of food items included in our pantry is given in Appendix A with their database identification numbers.

3.3 Mobile Humanoid Robot

As the intervention platform, we use a Pepper humanoid robot, [34] (Figure 1). Pepper is a 120cm-tall robot with 19 degrees of freedom which allows it to execute sophisticated gestures using its head, arms and body. In addition to these nonverbal communication channels, it also has speakers and microphones for verbal communication.

We control the robot with a Wizard-of-Oz system, [8]. During the experiments a research assistant, hidden in another room, controls the robot's behavior using a game controller and a user interface designed for this study. The experimenter observes the experiment through cameras and microphones placed in the virtual cafeteria and through another custom user interface.

For the physical behavior of the robot, we designed 6 custom animation sequences to cue food items located on the pantry shelves. The first three of these sequences are used when the robot is in a left-hand-side position with respect to the pantry and the participant as shown in Figure 2. The other 3 sequences are mirror images of the first three, and are used for the right-hand-side positioning. In each animation sequence, the robot cues a food item on either the upper, the middle, or the lower shelf in the pantry. These recommendation cues are composed of gazing and pointing at the target food. Additionally, the robot's position is aligned on a line in front of the pantry by the experimenter using the remote controller to be able cue the items placed along the shelves in different locations. This positioning itself serves as an additional communication modality for cuing the target food item.

For each *Physical Cuing* trial, the experimenter drives the robot from the home position (Figure 1 opaque robot) to the designated position for the current target food (eg. Figure 1 transparent robot) while the participant is waiting for the next order to appear on the touchscreen computer. The experimenter then waits for the participant to approach the pantry. Depending on how the participant approaches the pantry, the experimenter drives the robot towards left- or right-hand-side positioning with respect to the pantry and the participant in order to minimize likelihood of collision. The experimenter then triggers the animation sequence that is associated with the robot's current configuration and the location of the target food item on the shelves. Each full animation sequence follows the order of robot behavior as listed below:

(0) Execute idle posture and animations until the sequence is triggered
(1) Look at the face of the participant
(2) Look at the target food item on the shelf
(3) Lean forward and point at the target food item
(4) Look at the face of the participant
(5) Go back to the idle posture and animations

Once the participant complies with the robot and picks up the target food, the robot is driven back to its home position until the next *Physical Cuing* trial. If the participant does not comply, the robot is triggered to execute the same animation sequence two more times until the participant complies with the food recommendation or until the participant completes the current trial by serving the current lunch box.

For the experiments in the *Counselor* condition, participants conduct a counseling session with the robot before the meal assembly task starts. The counseling conversation with the robot is intended to 1) build rapport, trust, and therapeutic alliance with the robot, 2) establish the nutrition expertise of the robot, and 3) establish the role of the robot during meal assembly task. The conversation consists of a brief greeting and a few turns of social chat, a review of the current US guidelines for nutrition, a brief counseling dialog in which the robot assesses the participant's own dietary behavior and motivation for change, a discussion of what the robot will be doing during the meal assembly ("I will help you by occasionally making healthy suggestions."), and a statement of collaboration ("I look forward to working with you. Let's get to work!"). During the dialog, the robot uses appropriate conversational nonverbal behavior, including eye gaze and hand gesture. This dialog is also controlled by the experimenter who observes the interaction from a different room.

For the experiments in the *Bystander* condition, participants are told that the robot can move around the room to "help you with your food selections", and that the robot "will not talk while you are preparing your orders".

3.4 Participant Task User Interface

We also developed a user interface for the participants to receive orders through a touchscreen computer located within the virtual cafeteria (Figure 1). This interface displays 1) current order number, 2) orderer's name, 3) order type, 4) the list of ordered food items (if present for the current trial), 5) a "soft" countdown timer of 3 minutes, and 6) a "next order" button to proceed to the next order once the current lunch box is served. In Figure 3, an example frame from this user interface is displayed. For the orderer names, we created a name pool of 20 most common female and male names in <*location removed for blind review*>. We sample 10 from each gender and shuffle their order for each experiment. After receiving a new order participants are displayed a "soft" countdown timer of 3 minutes such that exceeding the timer would not terminate the current trial. We use this timer to discourage the participants from spending too much time on orders. The background color of the timer is switched to yellow once it reaches 1.5 minutes; and to red once it reaches 10 seconds.

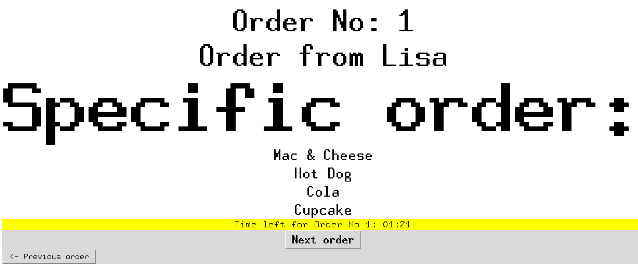

Figure 3: A sample frame from the user interface used to deliver orders to the participants. This particular frame is for a training trial where the orderer specifies the food items they request.

Before the participants are given their new order, they are shown "Waiting for order" text accompanied by a blinking three dots loading animation. We used a random delay between 5 and 15 seconds to simulate asynchronous arrival of orders. This delay not only served to improve the believability of the experience, but it also provided the experimenter with the crucial time needed to navigate the robot to its position during *Physical Cuing* trials.

The back-end of this user interface also handles randomized factors such as participant order types, Specific Order meal lists, food item to be cued by the robot, orderer names and delay durations. This information is also relayed to the wizard-of-oz control computer to be logged and displayed to the experimenter.

3.5 Measures

In order to analyze the effects of *ROBOT ROLE* and *CUING* factors on participants' food choices and attitudes towards the robot, we use a combination of quantitative measures. In Table 1, an overview of these measures is given.

Table 1: Experiment measures

Measure	Min. Score	Max. Score
Experiment logs		
Healthy Eating Index (per-trial)	0	100
Healthy Eating Index (per-experiment)	0	100
Compliance (per-trial)	False	True
Compliance rate (per-experiment)	0%	100%
Surveys		
Multiple Food Test-Choice†*	378	-153
Working Alliance Inventory-Bond	1	7
Trust in the Robot	1	8
Godspeed Questionnaire	1	7
Robot Attitude	1	7

(†): Measured in both pre- and post-experiment surveys.
(∗): Lower value indicates higher meal quality.

Our primary outcome measure for this study is the quantitative quality of the assembled meals, which we computed for each trial and each experiment. In order to score the quality of the assembled meals, we used the Healthy Eating Index (HEI), [26], which provides a meal quality assessment scheme that is independent of food quantity. Using HEI, 14 nutritional indices (eg. whole grains, sodium, saturated fats, etc.) are scored separately and summed up to obtain a final score ranging from 0 (poor quality) to 100 (highest quality). HEI scoring normalizes each individual index by total calorie intake. Thus, the measure can be used independently of the quantity of the meal combination to be scored. Our second quantitative measure is the participant compliance with the recommendation by the robot, determined through video review of participant behavior. We record compliance per trial (true/false) as well as computing compliance rate per experiment (0%-100%).

In addition to collecting quantitative data during the experiments, we administered self-report surveys pre- and post-experiment. The pre-experiment survey includes standard demographics questions and the Multiple Food Test-Choice questionnaire (MFT), [35], which evaluates the healthy food choice performance of the participants through an 18-item, multiple-choice scale. Each item in this scale asks the participant to select one out of four food items whose names and photographs are displayed under the items. The responses to each item can be interpreted in a 4-point scale (unhealthy-very health) or by using the Nutrient Profile Scores (NPS), which is provided in the survey toolkit. We use NPS values to evaluate the choices of the participants. The MFT questionnaire is also conducted post-experiment in order to assess the effects of *ROBOT ROLE* and *CUING* factors on the participants' food preference tendencies.

In the post-experiment survey, we also collect responses to several scales aimed to evaluate the (therapeutic) alliance between the robot and the participants. We use the Working Alliance Inventory-Bond scale, [22]; Godspeed questionnaire series, which measures perceived robot anthropomorphism, animacy, likeability, intelligence, and safety, [2]; Robot Attitude survey, which is a set of 8 single-item scales (Appendix B); and a composite Trust scale, [41].

3.6 Procedure

Participants were recruited from a social media site internal to our institution, and were required to be 18 years old and native speakers of English to participate. The study was approved by our institution's IRB, and participants were compensated for their time.

Participants were randomly assigned to either *Counselor* or *Bystander* sessions as the condition of the *ROBOT ROLE* factor upon enrollment. After arriving at the laboratory, they were given a briefing session about the study, given a training session on the meal order interface (§3.4), completed the experimental task, completed a post-experiment survey, and were debriefed. *Counselor* condition participants had a counseling session with the robot prior to starting the experimental task. Each experiment took approximately 60 minutes.

4 RESULTS

We recruited 23 participants (16 female, 6 male; ages 21-41, M = 25.9, SD = 4.2). One experiment was terminated due to technical problems, resulting in 22 participants completing all study tasks, with 10 in the *Bystander* condition and 12 in the *Counselor* condition.

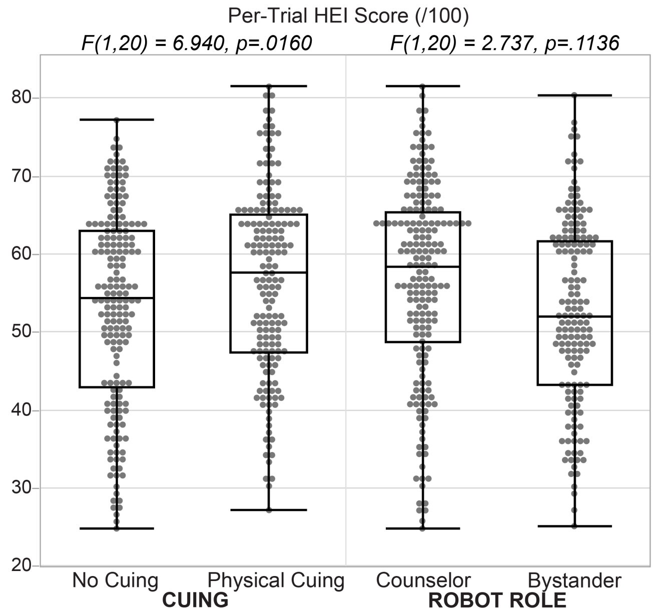

Figure 4: Results and the data distribution for the ANOVA on per-trial HEI scores.

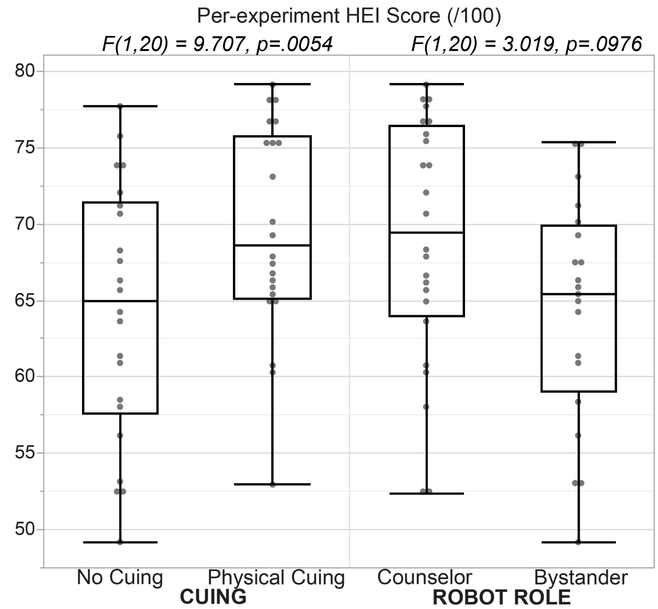

Figure 5: Results and the data distribution for the ANOVA on per-experiment HEI scores.

4.1 Effects on Primary Outcomes

In order evaluate the effects of the factors *ROBOT ROLE* and *CUING* on per-trial HEI food quality scores, we used analysis of variance (ANOVA). This analysis considered the *ROBOT ROLE* as the between-participant variable; and *CUING* as the within-participant variable (Figure 4). ANOVA results showed significant positive main effect of *Physical Cuing* on per-trial HEI scores ($F(1, 20) = 6.940, p = .0160$). We found trending effects of the *ROBOT ROLE* factor on HEI scores ($F(1, 20) = 2.737, p = .1136$) in the mean values of the data in favor of the *Counselor* condition.

HEI assesses the quality of a set of food items, and as larger quantities of food will span a broader range of HEI indices, it can result in more meaningful quality measurements. Thus, we also analyzed HEI scores for the total food items each participant selected in the 8 *Physical Cuing* and 8 *No Cuing* trial conditions for each experiment. Using the aggregate data, we ran another ANOVA. This analysis demonstrated a significant positive main effect of *Physical Cuing* ($F(1, 20) = 9.707, p = .0054$) and a trending positive main effect of *Counselor* ($F(1, 20) = 3.019, p = .0976$) on HEI scores (Figure 5). We did not find any interaction effects between the factors.

4.2 Effects on Compliance

During trials with *Physical Cuing*, overall participant compliance was 63.0% (SD 33.7%); with 60.3% (SD 33.9%) in the *Counselor* condition and 66.3% (SD 34.9%) in the *Bystander* condition. These compliance rates are all significantly greater than chance (assuming a comparison rate of 1/45 for random selection of the 45 food items), single sample t(21)=8.46, p<.001.

In order to test the effect *ROBOT ROLE* factor on compliance rates, we used independent means t-test. We did not find any significant effect on compliance rates ($t(19) = 0.405, p = .3448$).

4.3 Effects on Robot Attitude

We tested *ROBOT ROLE* factor's effect on attitude towards the robot using independent samples Mann-Whitney U test for single-item scales; and using independent means t-test for composite scales. We found significant and marginal effects on several robot attitude measures.

For the single-item scales, *Counselor* condition had significant positive main effects on satisfaction ($U = 94.0, p = .025$) and perceived knowledgeability ($U = 104.5, p = .002$). Additionally, we found trending positive main effects on ease of interaction ($U = 89.0, p = .051$) and the naturalness of interaction ($U = 88.5, p = .059$). For the composite scales, *Counselor* had significant positive main effects on trust ($t(20) = 2.334, p = .0152$) and perceived safety ($t(19) =, p = .0277$).

We did not find any effects on Working Alliance Inventory-Bond scale.

4.4 Effects on Post-experiment Food Choice

Independent means t-test analysis has shown *Counselor* condition had significant positive effect on post-experiment Multiple Food Test-Choice scores ($t(20) = 2.844, p = .0100$).

4.5 Effects of Attitude on Compliance

We analyzed the effects of self-reported post-experiment scales of attitude toward the robot on per-experiment compliance rates. For single-item scales, we computed Spearman's correlation coefficient; and for composite scales, we computed Pearson's correlation coefficient. The analyses have shown significant and marginal positive correlations between compliance rate and likeability ($\rho(20) = 0.443, p = .0383$), intention to work with ($\rho(20) = 0.420, p = .0516$), perceived knowledgeability ($\rho(20) = 0.378, p = .0824$), and relationship with the robot ($\rho(20) = 0.3969, p = .0674$). We computed Pearson's correlation coefficient for the composite measures, and did not find any significant effects.

4.6 Effects of Compliance on Primary Outcomes

We computed Pearson's correlation coefficient in order to check for effects of per-experiment compliance rate on HEI scores. Analysis did not show any statistically significant effects.

5 DISCUSSION

We found that robot cuing – moving to and pointing at healthy food items without talking – changed participant behavior and was effective in influencing healthier food choices, supporting **H1**. We also found that counseling by the robot, comprised of trust-building and nutrition role-setting dialog, led to greater self-reported trust in the robot by participants and improved food choice in the post-test MFT measure (assessing choice of food for themselves in a hypothetical task). However, the trust-building dialog only had a trending effect on food choice in the meal assembly task, providing only partial support for **H2**. In addition, trust-building did not affect compliance, which we hypothesized to be the mediator between our manipulations and healthy food choices.

Together, these results indicate that mobile humanoid robots can be successfully deployed in user environments to influence health behavior through proxemics and nonverbal behavior, in addition to counseling.

A possible explanation for the observed weak effect of counseling on food choice could be that trust and working alliance take more time, possibly over several interactions, to have influence, although other studies have demonstrated relational effects within the time span of a single experimental session [4]. It could also be that cuing simply has an overall much stronger effect that cannot be improved, at least with the brief counseling the robot conducted. The counseling also focused on participants' food choices for themselves, which could explain why there was an increase in MFT following counseling, but not food choice performance when choosing meals for others.

The lack of association between counseling and compliance, and between compliance and food choice, may have several explanations. Given the physical setup, participants may not have been able to tell precisely what the robot was pointing at, but still assumed the robot was communicating that it wanted them to pick something healthy, leading to low compliance but healthy food choice. If true, this indicates that the mere presence of a robot, or imperfectly executed deictic gestures, may still be effective at influencing health behavior. Our measure of compliance – relying on reviewing and coding participant behavior from low-resolution video – may also have been error-prone, resulting in compliance results that were inconsistent with other findings.

We also found that, while the counseling dialog led to significant increases in trust in and perceived relational closeness with the robot, it did not have a significant impact on the bond dimension of working alliance. This could be due to several items in the alliance measure being unrelated to trust and closeness, such as "The robot and I understand each other." and "I feel that the robot is not totally honest about its feelings toward me."

Overall, relative to theories of health behavior change and persuasion, we find that appropriate stimulus control [31] (cuing) does lead to healthier behavior, but that establishing credibility, relationship, and trust [6] [37] have a weaker effect, at least as operationalized in our study.

5.1 Limitations

Our study has several limitations, beyond the small convenience sample that may not be representative of the general population. Our virtual cafeteria may lack ecological validity and the results we find in this environment may not translate to other real-life contexts, such as grocery shopping or home meal preparation. Our use of fake food, while used in other nutrition studies [38], may have caused participants to behave differently than if they were choosing real food. Our single-session experiment likely suffers from novelty effects, and may not reflect what would happen in long-term repeated interactions. Finally, the use of a wizard-of-oz setup may have resulted in robot behavior that is different (better or worse) than a fully-automated system.

5.2 Future Work

There are many important directions for extending this research. We believe our virtual cafeteria is a great environment for evaluating a range of health counseling and persuasion strategies by a mobile robot, and future studies can be improved in many ways. The use of speech and/or the display on the robot could be used to help participants disambiguate items the robot is indicating, addressing some of our issues with low compliance. Assessing user health behavior after they leave the laboratory would address questions about ecological validity and the transfer-ability of behavior change. Inviting participants to engage in multiple experimental sessions would address questions about longevity and durability of results.

Future explorations could evaluate the use of just-in-time persuasive dialog in conjunction with cuing, to see if it is even more powerful at effecting persuasion than cuing alone. Knowledge of a user's health background and preferences could enable the robot to be more intelligent and/or persuasive regarding its recommendations. Finally, the robot could also use a wider range of verbal and nonverbal behavior in referring to health-related objects in the user's environment [9].

6 CONCLUSION

Our experiment demonstrates the feasibility and positive impact of having mobile humanoid robots influence healthy behavior by moving in a user's environment and indicating healthy choices at the time a user is making a health-related decision. This work moves beyond static robots that provide coaching to demonstrating the affordances of mobility and physicality in user interaction. We were able to demonstrate significant impacts even without the use of speech or other communication by the robot while cuing.

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