Iterative Robot Waiter Algorithm Design: Cocktail-Party Service Expectations and Social Factors

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ABSTRACT

Mobile robots carrying food in restaurants are here. What service behavior norms do people expect them to follow? This paper evaluates robot waiter algorithms and service parameters for a robot serving two participants at a simulated cocktail event, varying body-storming inspired context variables such as: "hunger level" and "relationship to each other," robot delivery algorithms (lead, follow, ambient), and participant pose (standing, seated). In the within-subjects design, pairs of people were given a series of context prompts, and told to participate as felt natural. Output variables included whether they took food and post-trial survey ratings of the robot. The results show a positive correlation between food taking (or feelings of obligation to take food) and human OR robot initiative, relative to a mixed-ambient algorithm with no explicit leader. The robot waiter that initiates is the clearest and most noticeable. There were also some challenges: people in conversation would sometimes forget or delay calls for cupcakes, ambient robot motion was hardest to notice, and bringing food one person ordered to the other was unforgivable. When in doubt, go to the middle. Finally, participants enjoyed the robot spinning, describing it as a dessert tray which attracted their eyes to the robot.

CCS CONCEPTS

• **Computer systems organization** → *External interfaces for robotics*; • **Computing methodologies** → *Cognitive robotics.*

KEYWORDS

robot social feeding, restaurant robots, theater method, iterative design, a/b testing, human-robot interaction, social robotics

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(a) Participants Watching Robot Waiter (b) Please Take a Cupcake <bump>

Figure 1: Pairs of participants *Standing* and *Sitting*

1 INTRODUCTION

Anyone that has ever seen someone offer a child a spoonful of food while sing-songing, "here comes the airplane!," can imagine how the-way-in-which a robot waiter offers food might impact the human's desire to eat that food and how they notice it. As an IEEE Spectrum article declared on the submission deadline for this conference, "Server robots have become a common sight in restaurants," and we are living at a time where there is an increasing integration of robots into human society across a wide variety of application spaces, physical appearances, and levels of interaction with people ([6, 20, 43]). [10] illustrates the utility of integrating social factors into prospective interaction algorithms. [8] explored in-room mobile robot food delivery, finding that sinusoidal paths attract people's attention. But what about scenarios in which there are multi-party interactions that a service robot needs to navigate?

Current robotics research has shown that social skills support the coordination success between people and robots ([37, 44, 46]), even for minimal social robots. Thus, behavioral programming that considers human-robot interaction across these many rising robot applications spaces is critical right now ([15, 29]). In this paper, we illustrate how one can use iterative, theater-inspired design methodologies to evaluate in-development robot behavioral software. In particular, we consider a robot waiter application context.

What would matter most – behaviorally speaking – for a robot delivering cupcakes to two people at a simulated cocktail party?

Should the robot *here-comes-the-airplane* to its customers, taking the social lead like a parent? Should the customers signal to the WaiterBot, telling our mechanical servants what to do, and avoiding the awkwardness of dealing with a real human? What are emergent norms? To address these questions, we utilized three exploratory design phases: (1) *Ideation:* use bodystorming to explore the application setup and behavioral research variables, (2) *Implementation:* implement ideas from previous into ROS-based path planning, robot-human communication systems, and behavioral algorithms, and, (3) *A/B/C Testing:* invite participants to act out scenarios of a cocktail party event across a variety of context variables, gaining data about robot waiter application expectations and algorithm viability. The results seed the importance of social factors in deciding how and where the robot offers food.

For example, ambient initiative resulted in very little food-taking, thus someone should take the lead. People are happy to initiate as long as they know they are in charge, OR they will also accept food from an approaching robot. In terms of delivery protocols, it is important to bring the food to a convenient location for transfer, so coherent side delivery impacts customer experience. Finally, social factors definitely matter: people that only knew each other a little bit liked getting food faster as it helped break the awkwardness, while ones that had known each other a long time sometimes found early delivery to be interrupting to their conversation.

2 RELATED WORK

In terms of current industry WaiterBots, **Servi** [3] (USA) and **Bellabot** [31] (China) are two pervasive platforms, reporting 10,000 and 56,000 units in use since the COVID-19 pandemic [7]. The former has two shelves for food, a "bus bin" for waste or composting products, and has operated in restaurants, senior living homes, and even arcades. Residents of one nursing home using this system said *they enjoyed being able to spend more quality time with the human servers themselves* [5]. Bellabot, with a four-shelf design, and screen-based ordering system also leverages sociability via display of an expressive cat-like face, voice-detection, and being able to detect head pats. Another bespoke WaiterBot design was reported to have an enclosed compartment to keep food items warm and clean, a draw bridge door that can be lowered to roll out a serving tray onto a table, and a lifting table to accommodate different table heights [9].

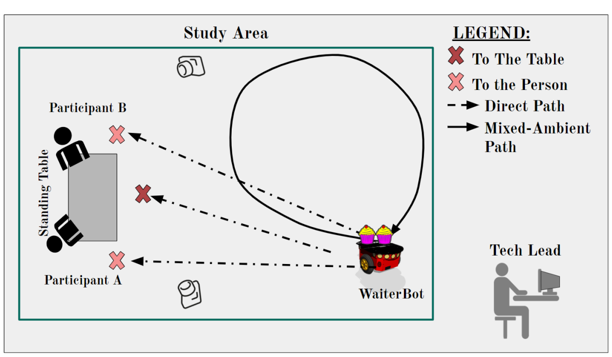


Figure 2: Experimental setup, illustrating varied robot motion pathways and end positions, in standing table condition.

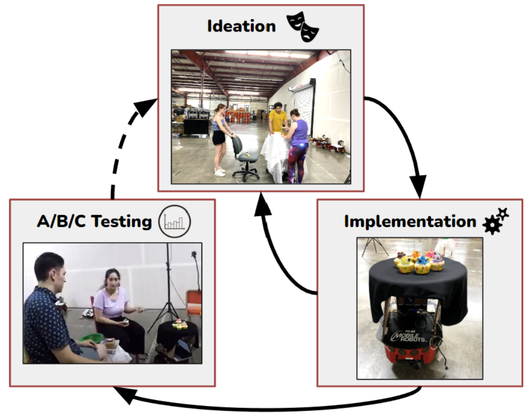


Figure 3: Application-specific service robot behaviors developed via iterative, theater design process: (1) Ideation, (2) Implementation, (3) A/B/C testing.

As technology for WaiterBots advance, more restaurants around the world are integrating it into their services. India opened its first robot-themed restaurant in 2017, where food is served to customers by WaiterBots clad in traditional saris [33]. There is a "robot restaurant complex" in Guangdong, China where 40 robots can prepare around 200 different food dishes and serve customers [11]. A Michelin-starred restaurant in Germany has a Bellabot named *Luigi* to enhance the service that the human staff provides to customers [34]. Even a local Mexican restaurant in Lima, Ohio utilizes a WaiterBot to bring food to its customers and entertain them with music and singing [45].

Past work indicates that robot waiter behaviors would benefit from adapting to user emotion [28], and inclusion of social norms such as serving elders before youth [22], and considering how the robot presents itself [27]. Pepper robots that adapted their spatial position based on face affect analysis (and online study data to train spatial norms) were rated as more enjoyable, sociable, and appropriate [28]. A Korean study conducted in a mixed-age group, found that robots serving elderly customers before young were seen as more *useful* and *polite* [22]. These expectations may vary depending on the context of usage (e.g., hotel WaiterBots may be perceived more positively than hospital WaiterBots [27]), use of such systems may vary by social class [47], and robot gender may impact customer interest, helping target explicit market segments [14], not unlike [40].

Beyond the scope of WaiterBots in particular, relevant prior work clarifies how to implement mobile robot expressive capabilities via motions [16, 36]. For example, using spatial distance between robot and human implicitly or explicitly communicates via 'proxemics' [18, 30], motion characteristics of it's orientation and trajectory impact people's attributions of robot state and goal [12, 17], and sequenced x,y,theta gestures such as spinning for joy are also informative [4, 25]. In one experiment a ChairBot used moving forward and backward to signal bystanders to sit at a particular side of a table [1] (also restaurant-host robot relevant); in another, ChairBots

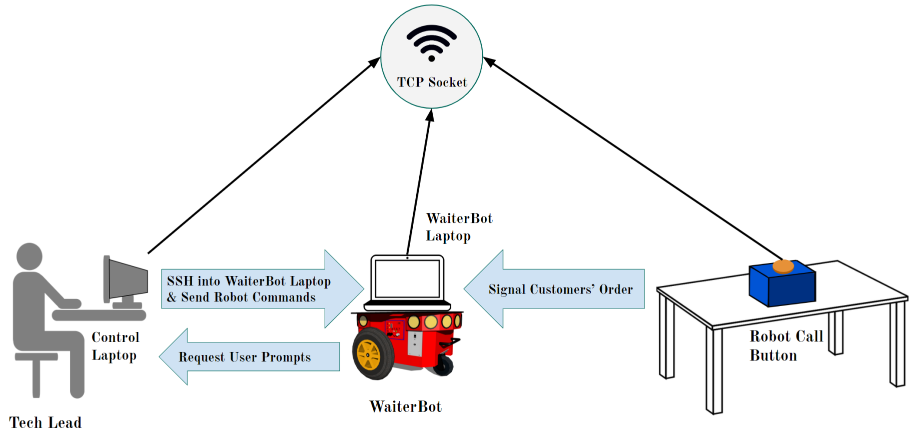


Figure 4: Diagram of the communication between the control laptop, button-calling system, and WaiterBot

used same gesture to non-verbally cue a human it needed to pass, [24]. The interpretation of robot gesture thus varies with task context. In robot arm motion design, both vector and timing influenced interpretation of robot goal, and the likelihood of response [23, 38]. Future robot waiters might also consider formation [2].

Iterative development of robot behavioral design has shown success in a variety of human contexts. In [38], researchers observed how humans handed flyers before developing robot handover protocols for A/B/C testing, [2] surveyed employees about expected factory robot communications before revising and evaluating robot light communications, and, both [42] and [19] use theater inspired methods. The former uses improvizational robot wizarding to act out social behaviors for robot furniture, and the latter has participants read out scripts illustrating varying social context and relationship backstories. We apply and extend in-person variants of these two design methodologies.

3 ITERATIVE DESIGN AND ASSESSMENT

The development of our WaiterBot behaviors and their in-context evaluations occurred in three steps, detailed in Fig. 3, including ideation, implementation and A/B/C testing. This section describes steps all of the steps involved in the methodology of this study.

3.1 Ideation Phase

We utilized theater-inspired methods to develop and evaluate our study's research variables. The goal was to explore socially-acceptable behaviors for robots feeding humans. This extends prior utilization of theater techniques in developing robot behavioral programming [19], utilizing metaphors from ethnography (e.g., [10, 13, 35]) and learning from demonstration (e.g., [26, 32, 39, 41]).

After the Institutional Review Board approved this study, three research members bodystormed programmable robot behaviors to implement and/or explore in our final robot software, drawing on similar prior approaches [19, 42]. One person acted as the "robot" by pushing around a wheeled chair with plastic cupcakes to simulate varying the robot's approach path, end positions, speeds, and perceived behaviors. Two others served as the "patrons" or study participants by acting out the remaining context, interpersonal, and intrapersonal variables. All took turns playing each role. For research variables relating to programmatic robot behavior, we considered transferablility of behaviors on the office chair to the physical robot. If the transferability was low, the variable was eliminated. The final list of research variables included initiative, food environment, and personal contexts, all inspired by restaurant and/or cocktail party experiences.

ROBOT SOFTWARE	
Who Initiates (Algorithm)	**To Where (End Pose)**
Robot Initiated Human Initiated Mixed-Ambient Initiative	To the Person To the Table
CONTEXT	
Cued Hunger Level	**Cued Relationship**
Hungry Not Hungry	Never Met Met a Few Times Old Friends
FURNITURE SETUP	
Standing Table Sitting Table	

Table 1: Research Manipulations. From our behavioral trials we evaluated the research variables presented above to be the most efficient in implementing in our study design.

3.2 Robot Waiter Implementation

Figure 4 illustrates the front and back-end technology setup for this work which includes robot hardware, button call system, ROS-based software, and a tech lead that responds live to the situation.

Robot Hardware: A Pioneer 3Dx robot with three degrees of freedom served as a physical base with a laser-cut serving table designed and installed atop the robot base. A tablecloth defines the food area as in catered events, also covering up the electronics.

Code	#	Definition	Example
Clear	2	Explicit confirmation of obligation as a result of personal context/behavior or the robot's action	"I definitely did because it was hovering around near me"
Some	1	Confirmation of obligation with situational modifiers (e.g., a little less, somewhat, etc.), as a result of personal context/behavior or the robot's action.	"I kind of was that time, [the robot] just sort of came up"
Neutral	0	Either no reference or unclear direction of response	"I thought I was suppossed to take it."
Little	-1	Denial of obligation with situational modifiers (e.g., a little less, somewhat, etc.), as a result of personal context/behavior or the robot's action.	"I guess I felt a little bit more, but no because I didn't really take it"
No	-2	Explicit denial of obligation as a result of personal context/behavior or the robot's action	"Not even a little bit"

Table 2: The set of obligation codes that we used to analyze obligation levels in food taking.

Button-Calling System: The call system consisted of a push button, Arduino MKR WiFi shield, and a breadboard, delivering "request for service" functionality. The button-calling system had come up as a robot summoning mode during our bodystorming process, and was selected both because it was fairly easy to implement technologically, and because if it's similarities to restaurant ordering tablets (e.g., [21]), as well as table-integrated drink reorder buttons (e.g., in Korea). For the button to communicate with the robot, the WiFi shield connects its local network to WaiterBot's onboard computer over a Transmission Control Protocol (TCP) socket and designated port. If participants push the button (i.e., signaling a "request for service"), the client-server (MKR wifi shield) will send a message that the button has been pressed to WaiterBot. Once the message is received, the request is published using ROS nodes. Upon receiving the request, WaiterBot will move based on the trial-configured robot software.

WaiterBot software utilizes Robot Operating Systems (ROS)-based geometry and odometry libraries to facilitate navigation. Specifically, the Pioneer 3Dx base runs ROS kinetic with standard geometry_msgs and Odometry ROS libraries. In the *human-initiated* or *mixed-ambient initiated* condition, WaiterBot will remain idle – either not moving or circling (see Fig. 2 "mixed-ambient path") – until participants press the call button. In *mixed-ambient initiation*, the robot will move in a circle until either a timeout period of three minutes is complete, or the user presses the button. After any algorithm, WaiterBot will return to its home position when the tech lead prompts the robot after either return condition is satisfied. The "To Where" algorithm stores points representing the *end position* of the robot across all "Furniture Setup" manipulations (see Fig. 2).

3.3 A/B/C Testing

During the experiment, two participants were instructed to converse with each other as they would naturally at a cocktail party, each trial beginning with a specific set of context variables, e.g., "for this trial, you are both hungry and have met a few times." To ease their ability to come up with topics, they selected a slip of paper from a hat. Whatever the backstory, all trials involved a robot with a tray of plastic cupcakes. Participants were requested to respond as they felt appropriate, e.g., taking or not taking cupcakes.

3.3.1 Research Manipulations. The full list of research manipulations is presented in Table 1. The "Who Initiates" variable included three levels: robot-initiated, human-initiated, and mixed-ambient. In *robot-initiated*, the robot initiates the food delivery by driving toward the participants while talking. In *human-initiated*, participants were provided the call button and could call WaiterBot at any time throughout the trial. Finally, in *mixed-ambient initiative*, the robot circles in the general area, and the participants may use the call button if desired. When "To Where" was *to-the-person*, WaiterBot randomly approached person A or B (pink X's in Fig. 2), while *to-the-table* heads to an area between the participants (red X). The context variables–"Hunger Level" and "Relationship" represented backstories to facilitate food taking and conversations and the general environment setup. Finally, the "Furniture Setup" included *standing table*, where participants stood at the corners around a high table, and *sitting table*, wherein participants were sitting in chairs (see Fig. 1).

3.3.2 Assessment Measures. Research metrics included participant food-taking, reports of feeling obligated to take food, and ratings of robot attributes. For *food-taking*, we recorded whether participants kept a plastic cupcake from the WaiterBot by the end of the trial. *Obligation* to take food was assessed by asking: "did you feel inspired or obligated to take food?" after each trial, using the obligation codes in Table 2. Finally, robot attributes ratings were collected via 7-point, anchored-scale questions about WaiterBot's politeness, naturalness, and patience levels, e.g., rating the robot as very, mostly, or somewhat polite.

3.3.3 Procedure. Experiments consisted of 6 trials, each exploring a permutation of the robot algorithm and context variables, followed by brief surveys and a semi-structured after-experiment interview. In all trials, participants had access to a hat of conversation starters and a movie clapper with the exact "Relationship" and "Hunger Level" manipulations to act out during the trial. Finally, if applicable, the conductor added the call button based to the table.

The tech lead initialized the appropriate robot software at the start of each trial to the "Who Initiates" and "To Where" variables and prompted WaiterBot to leave its delivery location if participants took food or after 30 seconds of no participant interaction. When WaiterBot returned to its starting position and stopped moving, the study conductor began the post-trial survey.

Once participants completed all trials and post-trial surveys, the study conductor would perform the post-experiment interview.

Throughout the study, two video cameras (visible in Fig. 2) recorded participants' behavioral responses.

3.3.4 Data Analysis. Statistical analyses were conducted on our dataset for main and interaction effects related to food taking, obligation to take food, and perceived robot attributes. Single variable manipulations utilized a Kruskal-Wallis test due to non-normal data distributions, confirmed by the Shapiro-Wilks test. One exception was using an ANOVA analysis on *politeness* given its close-to-normal distribution. For interaction effects between research manipulations (e.g., "Who Initiates" x "To Where"), we used Wilcoxon paired tests as almost all interactions were non-parametric. The exception was analyzing *took food* given its binary data. As such, we used Fisher's exact test, converting data into a 2x2 table with rows being *took food* and *did not take food* and columns as the interaction effects (e.g., *hungry* x"Who Initiates" and *not hungry* x "Who Initiates"). Qualitative analysis of participants' reactions and experiences is used alongside exemplar storytelling to add insight to participant experience of the next section's statistical results.

4 RESULTS

This section presents the statistical results of the analysis of 72 data points (6 trials x 12 participants) for food taking, obligation levels, and perceived robot behaviors for single variable and paired variable interaction effects (see Table 3). Six men and six woman interacted with the WaiterBot throughout the study with ages ranging from 18-35. Pre-existing relationships between pairs of participants ranged from "never met" (16.7%) to "significant other" (16.7%), to "some form of acquaintance" (16.7%), and "friendship" (50.0%).

4.1 Survey Responses

4.1.1 Patience. "Furniture Setup" was a significant indicator of participant *patience* ratings (H(1)=6.617, p = 0.0101**), with people most patient in the **sitting table** condition, perhaps because they felt more comfortable. When we further considered the interaction effect between "Furniture Setup" x "Relationship" (t(35)=112.5, p=0.0638†), we see the lowest patience for the robot in the **never met** condition. One **sitting table** participant reported, "we are **old friends**, we're happy, we're chilling, we're talking."

4.1.2 Naturalness. "To Where" significantly predicted participant ratings of robot *naturalness* (H(1)=4.371, p=0.0365*), with **to the table** rated highest, which participants described as robot as offering food to both participants. One participant explained, "if we were sitting, then [the robot] coming to [the opposite] side of the table probably would've completely inhibited my want to go walk around to go get [food] unless I was really hungry." "To Where" x "Furniture Setup" significantly impacted perceived *naturalness*. Finally, "Who Initiates" trended towards significance (T(35)=113.0, p=0.0644†), with one participant reflecting that an initiating WaiterBot "...felt more like a traditional waiter at a cocktail party, walking around with a tray of food."

4.1.3 Politeness. "To Where" trended toward significance, with a robot delivering **to the table** rated as more polite than **to the person** (F(1, 70)=3.882, p=0.0528†), likely because that sometimes resulted in going to the wrong person. "Who Initiates" x "To Where," further predicts politeness, with participants perceiving all deliveries **to the table** as more polite (H(35)=110.0, p=0.0532†). Participants attribute higher politeness to all **sitting table** conditions, thus, "To Where" x "Furniture Setup" was considered the most polite when delivering **to the table** while participants were seated.

4.2 Food-Taking and Feelings of Obligation

4.2.1 Initiative Results. : "Who Initiates" (i.e., whether the human, robot, or (n)either initiated) was a significant predictor of *food taking* (H(2)=11.29, p=0.0035**). The **human-initiated** (μ=66.7%) and **robot-initiated** feeding (μ=58.3%) outperformed the **mixed-ambient** condition (μ=20.8%), with multiple participants describing the mixed-ambient initiative with more negative anthropomorphic descriptions, such as being "distracted" or "roaming without a purpose". Unlike "Hunger Level", *obligation* results for "Who Initiates" were not significant, even though some participants noted such feelings. One participant said, "I called it, and it came, so, of course, I had to take it," which may indicate that people will feel an obligation to take food after calling it over.

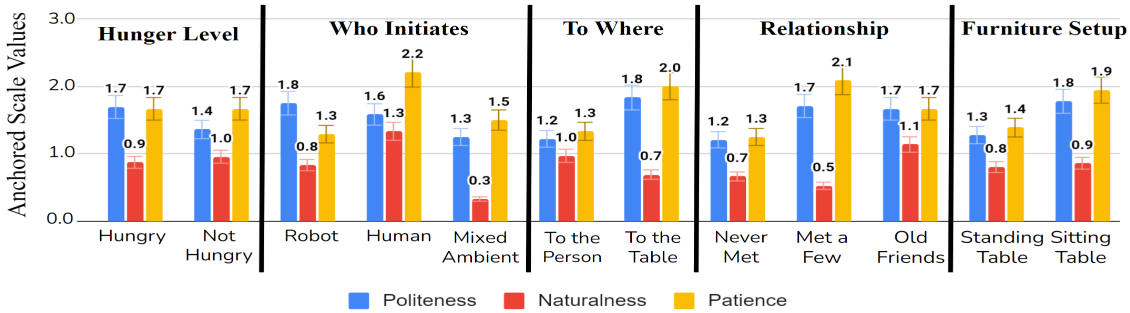
4.2.2 To Where Results. "To Where"–WaiterBot's stopping pose relative to participants and the furniture– did not significantly impact on participant *obligation* (H(1)=0.0, p=1.0) or *food taking* (H(1)=0.0548, p=0.8148). However, multiple participants expressed discontent when the WaiterBot went to one side instead of the middle. If we review Fig. 6, we also see higher numerical food-taking for consistent delivery, and much higher not-food taking for inconsistent-side delivery. Convenience of food location and experience of robot politeness may impact customer experience.

4.2.3 Hunger Level Results. : Participant "Hunger level" was a very significant predictor of *taking food* from the WaiterBot (H(1)=52.67, p≤0.0001**). The **hungry** condition (μ=0.917) notably outperformed the **not hungry** condition (μ=0.056) with many participants stating hunger as a motivating factor in obligation to take food (H(1)=5.19, p=0.0227*). Despite this, *obligation* scores for **not hungry** (μ =0.417) surpassed those for the **hungry** condition (μ =0.292), with one participant stating, "I wanted to be the one to give the robot purpose, but also we're not hungry, so we couldn't [take the food]."

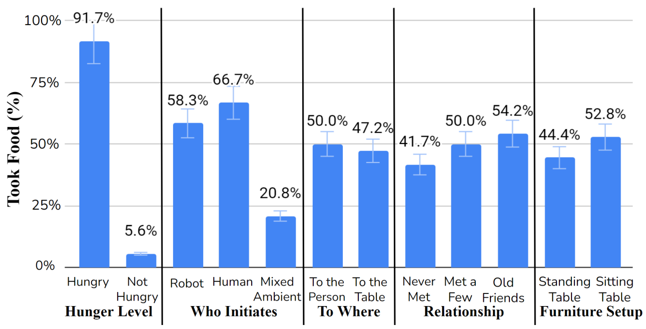
4.2.4 Relationship and Furniture Results. Neither participant "Relationship" nor "Furniture Setup" impacted *food-taking* or *obligation -to-take-food*. Though, one participant explained, "I was a little less distracted in the conversation [not knowing each other well] compared to if we were **old friends**. So I noticed the robot quicker." With respect to furniture, participants said the WaiterBot's height was more suited more to **sitting** than **standing**.

4.2.5 Significant Interaction Effects. "Hunger Level" x "Relationship" (p≤0.0001**) interacted to very significantly impact *food taking*, with all **hungry** conditions notably outperforming all **not hungry** conditions regardless of "Relationship" for *food-taking*. **Hungry** x **met a few times** saw participants taking food from the WaiterBot every time, while **not hungry** x **never met** or **met a few times** saw no participants taking food (Fig. 5b). More than one participant noted to the study conductor that it felt more awkward to "eat" in front of someone they don't know.

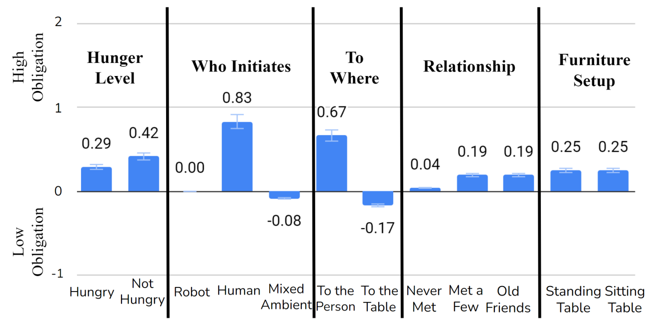
"Hunger Level" x "Furniture Setup" very significantly predicts *food taking* (p≤0.0001**) with all instances of **hungry** resulting in more food-taking than **not hungry**. For **standing table**, no participants took food from the WaiterBot while acting **not hungry**



(a) **Robot Attributions:** Centered To-the-Table Robots more Polite, Seated Participants more Patient



(b) **Food Taking**: Hunger Level Predicts Cupcake Taking



(c) **Obligation to Take Food:** Highest if Human Called Robot

Figure 5: Mean values for robot attributions, and participant food-taking and sense-of-obligation to take food.

	Taking Food	Obligation	Politeness	Naturalness	Patience
Hunger Level	**$p \leq 0.0001^{**}$**	**$p = 0.0227^{*}$**	$p = 0.2678$	$p = 0.2800$	$p = 0.7005$
Who Initiates	**$p = 0.0035^{**}$**	$p = 0.124$	$p = 0.428$	$p = 0.0579^{\dagger}$	$p=0.2700$
To Where	$p = 0.8149$	$p = 1.0$	$p = 0.0528^{\dagger}$	**$p = 0.0365^{*}$**	$p = 0.2270$
Relationship	$p = 0.6813$	$p = 0.8096$	$p = 0.4013$	$p = 0.8933$	$p = 0.4570$
Furniture Setup	$p = 0.4824$	$p = 0.9032$	$p = 0.0650^{\dagger}$	$p = 0.8118$	**$p = 0.0101^{**}$**
Who Initiates x To Where	$p = 0.8136$	$p = 0.7552$	$p = 0.0532^{\dagger}$	$p = 0.0649^{\dagger}$	$p = 0.5380$
Who Initiates x Furniture Setup	$p = 0.6376$	$p = 0.9825$	$p = 0.1166$	$p = 0.9917$	$p = 0.1165$
To Where x Furniture	$p = 1.0$	$p = 0.9917$	$p = 0.0598^{\dagger}$	**$p = 0.0488^{*}$**	$p = 0.1902$
Hunger Level x Relationship	**$p \leq 0.0001^{**}$**	$p = 0.0504^{\dagger}$	$p = 0.3239$	$p = 0.4109$	$p = 1.0$
Hunger Level x Furniture Setup	**$p \leq 0.0001^{**}$**	**$p = 0.0445^{*}$**	$p = 0.2427$	$p = 0.3920$	$p = 0.9196$
Furniture Setup x Relationship	$p = 1.0$	$p = 0.9738$	$p = 0.1158$	$p = 0.8269$	$p = 0.0638^{\dagger}$

Table 3: The p-values relating input variables and their interaction effects to food-taking, obligation, and robot attributes

(μ = 0%) compared to taking food 88.9% of the time when **hungry**. "Hunger Level" x "Furniture Setup" significantly impacted the *obligation* to take food (T(35)=125.5, p=0.0445*). After a bump, one said, "[the robot] kissed my leg, so it's rude not to take [food]."

4.3 Qualitative WaiterBot Experience

Researchers in anthropology, psychology, and robotics use ethnographic studies to collect behavioral data through "fly-on-the-wall" observations [10, 13, 35]. Learning by demonstration systems also benefit from modeling what factors should be tracked [26, 32, 39].

To clarify participant experience, we conducted grounded coding over participant responses to the question, *Did you feel inspired or obligated to take food?* (N=285 responses), wherein participants often discussed wide observations of their experience of each trial:

> "And then it stopped in front of me. That is a big indication [the robot] wants you [to take food]. Its purpose is to want you to take [food] because it stops in front of you and it's within hand range... and after I took the cupcake, it spun nicely. Very smooth."

	Took Food?		
	Yes	No	Total
Approached Same Side	8	4	12
Approached Opposite Side	7	17	24
Total	15	21	36

Figure 6: Foodtaking in consistent-side (robot goes to person ordering) and inconsistent-side delivery (to other person).

Figure 7: Pioneer robot with LaserCut Chassis.

The quotes from the post-trial surveys allude to broad participant ability to imagine themselves at a cocktail party in varied states. We highlight trends of how participants responded to algorithm conditions by categorizing (1) participant responses as good/bad/weird service ratings, and, (2) attributions of robot-service-noticiablity; e.g., if the participant said the robot was rude, that line would receive 'bad service' and 'notice' +1 flags, whereas if they said, "what robot?," no service flags would be annotated, and notice would be labeled -1. Robot initiative was most noticeable (60% mention), whereas in human-initiated and ambient noticiability was only 18% and 15%. Service was described with positive words in 26% of our robot initiative trials, 18% of person-initiated, and 15% of the ambient robot motion trials.

Several explained how assigned cues related to their food service desires: "*I feel that if I was hungry and with somebody I had never met before, then I would be looking for the food robot the whole time. Escape makes it sound bad, but to ease the situation..*" Contrasting the met-a-few-times condition, another related, "*because we were old friends [in this trial], it felt more comfortable to do experimental things.*" Social influence was also evident: "*It was approaching someone who I was talking to and [that person] offered me [food], definitely motivating me towards getting a cupcake.*"

Figure 8: Final Presentation with Cupcakes

5 DISCUSSION

The WaiterBot user study results provide insights into various functional and social recommendations for future integration of robot servers. Both this paper and a prior study by [28] aim to explore *how* and *where* service robots should offer food to customers. While McQuillin et al.'s paper uses a data-based approach to their study, the WaiterBot paper utilizes a theater-inspired approach, in both the bodystorming and the evaluation phases, asking participants to act out scenes. Furthermore, while McQuillin et al. explores the robot waiter's positioning relative to human response, our study focuses on perceived robot character and sociable interaction. The differences result in two papers that potentially complement and add onto each other.

The WaiterBot study provides an end-to-end demonstration of how body-storming, implementation, and A/B/C testing sequences can flexibly push forward robot behavioral prototyping. Overall, the results show that (1) people are happy to take food from robots and feel social obligation, and (2) that food service is context dependent.

In terms of **food-taking**, and feelings of obligation to take food, customers were most likely to take food from the robot that they ordered (67%), finding the mixed ambient robot condition confusing as if the robot was distracted, though robot-initiated feeding was also effective more than half the time (58%). Obligation occurred most often when the robot was in proximity of the participant, or wherein the person had initiated the order. Interestingly, many people felt obligated to take food even if they were not hungry, explaining it was to reward the robot efforting.

Food service is also context dependent, however, wherein context might involve venue setup (e.g., standing versus seated tables), delivery target (e.g., to a particular person versus the center of the pair), who initiates an order (e.g., always robot, always human, or mixed/ambient), and was even effected by the relationship of the pair themselves (e.g., old friends, met a few time, or never met. In terms of **patience**, people were most patient with the robots in pairs that had only met a few times, wherein the human initiated, and when customers were seated rather than standing. Not hungry people were not less patient in this case.

6 CONCLUSION

In this paper, we introduce a ROS-based cupcake delivery system that can offer service to two people sitting or standing in a cocktail party context. Participants intuitively responded to the robot waiter, which was only sometimes perceived as interrupting their conversation. They enjoyed the robot's unique abilities, and sometimes used the robot as a distraction from the discomfort of spending time with someone they barely knew. Major results:

In terms of **politeness**, people rated the robot to be more polite when they were hungry than not hungry, perhaps because they appreciated its services more, and found a robot that initiated an order more polite than having to call over the robot themselves. **Naturalness** means were low positive, with people finding human-initiated orders and attending a robot restaurant with old friends most natural. Furniture setup mattered too. Bringing the dish to the center of the table was rated as polite, with customers feeling more patient, over bringing the cupcake to just one customer.

Those with high hunger were 16 times as likely to take food as those with low, and food-taking scaled with how well people knew each other, with those that were meeting for the first time taking the least. Finally, some interaction effects occurred. For example, furniture-type only impacted food-taking in combination with participant hunger-level and prior-customer-relationship.

When in conversation, people may ignore the WaiterBot entirely. When feeling awkward, people just meeting each other say they welcome its interruption. Limitations of this work are that it is not yet a true restaurant context, the food was plastic, and that the robot itself was not food-safe. All considerations that can be included in future expanding evaluations.

This work also demonstrates the viability of the participatory acting methods in exploring prospective human-robot behavioral designs. Future robot designers trying to define and implement socially acceptable robot behaviors in different environments can utilize **bodystorm-implement-test** iterative methods. The expansive exploration during bodystorming highlighted useful potential WaiterBot features, as well as context variants for A/B/C testing.

Acting-inspired techniques allowed people of varying ages and technical backgrounds to help advance the field of HRI, enabling observational analysis and suggesting factors to be included in future adaptive systems. After all, theater taps into the human ability to imagine, and everyone eats. Given our experience, however, we encourage future researchers to track *imagination cognitive load*, i.e., the complexity of what participants can intuitively act out.

Future work can continue to explore the ideation and refinement of service robot behavioral design in deployed public settings. While the present application space was a cocktail party, similar rulesets could be developed for fancy dinners, banquets, or even assistive feeding applications. In fact, a taller version of the WaiterBot was deployed to interact with people by delivering candy and the ability to draw (paper and crayons) for 2023 Halloween, adjusting the robot table height to better serve standing individuals.

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