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Using Nonverbal Signals To Request Help During Human-Robot Collaboration

Elizabeth Cha and Maja Matarić

***Abstract*— Non-humanoid robots are becoming increasingly utilized for collaborative tasks that rely on each collaborator's ability to effectively convey their mental state while accurately estimating and interpreting their partner's knowledge, intent, and actions. During these tasks, it may be beneficial or even necessary for the human collaborator to assist the robot. Consequently, we explore the use of nonverbal signals to request help during a collaborative task. We focus on light and sound as they are commonly used communication channels across many domains. This paper analyzes the effectiveness of three nonverbal help signals that vary in urgency. Our results show that these signals significantly influence the human collaborator's and their perception of the collaboration.**

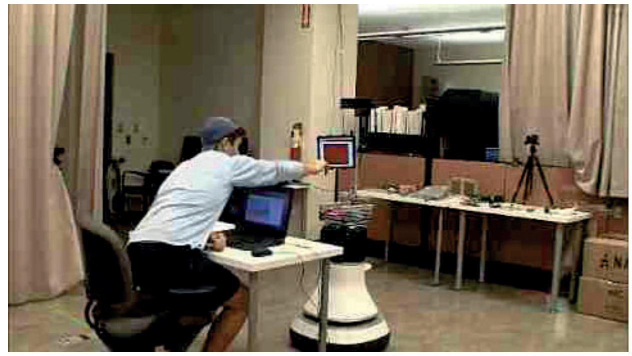


Fig. 1: A participant responds to the robot's nonverbal help request.

I. INTRODUCTION

Collaboration requires multiple entities to work together to achieve a shared goal [1], [2]. For this to succeed, participants must effectively coordinate their actions [1]–[3]. These *joint actions* often require additional perceptual, cognitive, and motor processes as collaborators must effectively communicate their knowledge, intentions, and goals [1], [4].

Human-robot collaboration (HRC) faces similar challenges as robots must effectively communicate their mental state while correctly interpreting the actions of human collaborators [2], [4]–[6]. Although past work in HRC has often focused on tightly-coupled tasks that require collaborators to work together to perform the same action, such as assembling furniture [5], there are still numerous technical challenges associated with coordinating precise physical actions.

Alternatively, human and robot collaborators can share a loosely-coupled task, engaging in complementary actions towards a shared goal [1], [7]. For instance, in a restaurant scenario, the robot can take on the role of waiter, coordinating responsibilities of taking orders and delivering food with those of the human chef who prepares the orders.

In this work, we focus on *loosely-coupled tasks that require complementary actions of non-humanoid robots.* Such collaborative systems already exist and span many application domains, including manufacturing and service [5]–[7].

Since each party acts separately in loosely-coupled tasks, situations arise when the robot is unable to complete its actions due to limitations in its knowledge or capability. To overcome this, it is advantageous for the robot to seek help from its human collaborator as they are often in close proximity, knowledgeable about the robot's goal, and motivated to assist.

Humans are experts in assessing one another's availability and effectively utilizing subtle and non-subtle cues, such as gestures and sounds, to communicate the need for assistance [8], [9]. Most robots, however, lack the appearance, modalities, or capabilities required to replicate such signaling [10], [11]. Consequently, a robot asking for help can be distracting and obtrusive, lowering efficiency and annoying its collaborators [12]. Hence, this work addresses the problem of *how non-humanoid robots can effectively and appropriately utilize nonverbal communication signals to request help in a collaborative task setting*.

A key challenge in creating help-seeking signals is balancing the needs of the human and robot. While it is advantageous for the robot to always immediately receive the requested help, this can slow down the collaboration and annoy the human. Instead, the robot must take into account a number of factors, including urgency, availability, and annoyance, when signaling for help [8], [9], [13].

To explore the effectiveness of nonverbal signaling for help in a HRC task, we developed a set of signals that utilize two common communication channels–light and sound– to convey varying levels of urgency. We evaluate the effectiveness of these signals on a collaborative task through a user study.

The results of the study show that these signals influence both the human's response behavior and their own actions leading up to the help request. We also engaged in a post-study design session with the study participants, to explore how to refine the tested help signals to be more expressive and acceptable to users. We present the objective, subjective, and design discussion results of the user study.

II. BACKGROUND

Although the mechanics of collaboration have been extensively explored, human-robot collaboration poses additional challenges as humans facilitate collaboration by using nonverbal cues that are difficult for robots to both interpret and produce [1], [2], [5]. To better understand and address these challenges, this work draws from the large body of research in collaboration and nonverbal signaling, as well

Elizabeth Cha and Maja Matarić are with the Interaction Lab in the Department of Computer Science, University of Southern California, Los Angeles, CA 90089 echa,mataric@usc.edu

as communications research in psychology, animation, and human factors. We briefly survey these areas in this section.

A. Collaboration

Human-human collaboration has shown that the ability for each party to coordinate their actions greatly impacts the success of the collaboration [1], [2], [6]. Humans utilize both verbal and nonverbal cues to signal information, such as their knowledge, goals, and intent, that is important for achieving a high degree of coordination [1], [2]. Many of these signals are unintentional to the extent that people are unaware of using them until they are pointed out [1].

Robots, on the other hand, typically only take action when they have a specified task or goal. Hence, a greater degree of thought and planning is required to create fluid collaborations humans are able to achieve [1]. An extensive body of work explores how to best coordinate people and robots collaborating, including using shared task representations [14], perspective taking [2], and anticipatory action [12]. Although these methods help the robot to better plan its own actions, for the collaboration to succeed, the human collaborator must also attempt to understand the robot's state of mind, anticipate its actions, and plan accordingly.

This requires robots to communicate key aspects of mental state, such as intent, that allows for successful collaboration between humans.

B. Communicating Mental Status

Humans continuously utilize nonverbal signals that give insight into their state of mind for both social and task-oriented interactions. Subtle cues, such as body pose or changes in voice, can indicate a wide range of intents, knowledge, or emotional states.

Recently, several works have looked at communicating intent, a key aspects of mental state [11], [15] that is increasingly important as robots start working with and around humans. Motion has become an popular channel for expressing intent as even simple animations can ellict strong attributions of intent [16]. Studies have shown that human observers can infer a robot's goal from its motion [11], [15], [17].

Robot motion has also been shown to convey other aspects of mental state, such as affective state [18]. The challenge with using motion is that it cannot interfere with the robot's ability to perform the task at hand. Moreover, additional limitations in the platform, task, or environment can make it impossible to use motion in some situations.

Other popular modalities for communicating affect include speech, linguistic cues, facial expressions, and body posture [19]. Many non-humanoid robots, however, lack these channels, and there are significant challenges for generating expressive realistic cues across many scenarios [10]. Therefore, there is a need to explore alternative communication channels for enabling expressive and collaborative robots.

Extensive work in design and human factors has looked at creating various signals using audio cues, visual cues, and haptics [20], [21]. Due to the safety concerns of having robots operating in close proximity to humans, we chose to focus on audio and visual cues. Machines and appliances often use such cues, in the form of sound and light, to signal various states (e.g., error, idle, ongoing, or completed task) [22]. In high risk tasks, such as air traffic control, such cues are critical to safety and success. Many of these signals have been learned over time, while others mimic human behavior. Thus, our goal in this work is *to explore how we can create similar light and sound signals for use in human-robot collaboration*.

C. Requesting Assistance

In many cases, the robot's capabilities and knowledge are not sufficient for completing the task, either individually or in a collaboration [23]. Hence, assistance from humans may be critical to the robot's success, making it important for the robot to be able to signal when it needs help [8], [13], [23].

The collaborative context is unique in that this is critical to not only the robot's success, but the human's as well. When requesting help from a bystander, the robot must be careful to provide a clear, polite request that the human can understand [13], [23]. When working on a collaborative task, however, shared goals and knowledge allow each party to request help in a more succinct and efficient manner.

Asking for help can be broken down into three phases: 1) get the responder's *attention*, 2) *alert* the responder that help is needed, and 3) put forth the *request* [8], [9], [13]. Since the semantics of the request are often dictated by the scenario, we focus on only the first two phases.

A natural mechanism for getting attention is through motion. The robot can either use a trajectory that engages the human or puts them in close proximity for subsequent signaling. Unless the robot uses a secondary signal, however, the human may have to wait until the end of the approach to confirm that the robot needs help [9]. Hence, another goal of this work is *to research to appropriately use a secondary signal along with motion*. We choose to utilize a simultaneous combination of light and sound as both are good at capturing attention, can provide a large amount of information, and can be used in combination with motion.

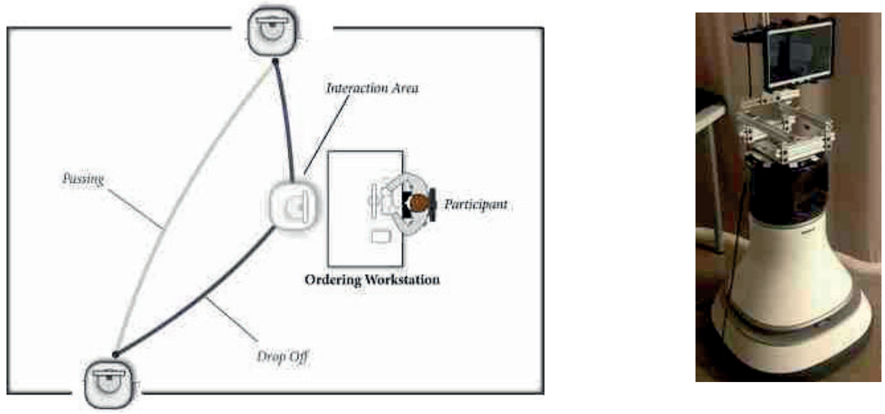
III. HYPOTHESES

As a first step towards our goal, we created a set of signals to request help using light and sound. We vary the signal parameters to convey different levels of urgency of the help request. We predict that the request scenario (i.e., the signal urgency and the responder's availability) will affect the collaboration both objectively and subjectively. We also expect that participants will prefer that the robot balance the annoyance of the signal with the urgency of the request.

H1: Design of Nonverbal Signals. *Non-humanoid robots can effectively utilize light and sound to create nonverbal signals that convey urgent and non-urgent requests for help.*

H2: Objective Request Metrics. *The request scenario significantly affects the time it takes for the human collaborator to react and respond to the request.*

H3: Subjective Request Metrics. *The human collaborator's perception of the help interaction is affected by the request scenario.*



(a) (b)

Fig. 2: An overview of the experimental study design: (a) An overhead view of the experiment setting, (b) an iRobot Ava platform, modified to hold a tablet (pink order container not shown)

IV. EXPERIMENTAL DESIGN

A. Collaborative Task

We considered several constrains when choosing a collaborative task to explore help requests. First, as the focus of the study is on *how* to ask for help, participants must be motivated to assist the robot. To ensure this, participant's success should depend on the robot's ability to perform its part of the collaborative task.

Second, to create consistency, we minimized the robot error by 1) limiting the robot to simple actions within a confined area and 2) reducing the need for accurate perception.

Third, the task should be realistic. Simulating a real world task creates a more authentic experience that motivates performance and increases willingness to collaborate.

To satisfy these constraints, we chose a task in a food service scenario: the participant and robot work together to collect and input meal orders. Since the study took place in a university research lab, participants were told the orders were from the surrounding offices on the same floor. In order to remove potential task inconsistencies, the robot and participant are given separate assignments: the robot drives around, collecting meal orders, and the participant inputs orders dropped off by the robot into a computerized system.

The robot also periodically requests help from the participant in retrieving a name or room number from the building directory. The robot is idle only while waiting for the participant to take a batch of meal orders from it or to answer its help request. The participant is idle and *available* when they have no new orders to put in the system.

Fig.2 shows a diagram of the experimental set up. The ordering workstation consists of a single table, chair, and computer located in the middle of a room with entrances to both the right and left. During the study, the robot enters the room on either side to perform one of three actions: drop off a batch of meal orders, request help from the participant, or pass between the exterior rooms. When dropping off orders or requesting help, the robot moves via a straight line trajectory (with a slight arc for naturalness) from the entrance to the "interaction area" in front of the participant's workstation. After the interaction is complete, the robot leaves the room using the same trajectories. The robot never moves behind the workstation to prevent potentially startling the participant. We chose these paths as the distance to the workstation is short and they are consistent with prior work in robot approach behaviors [8], [24].

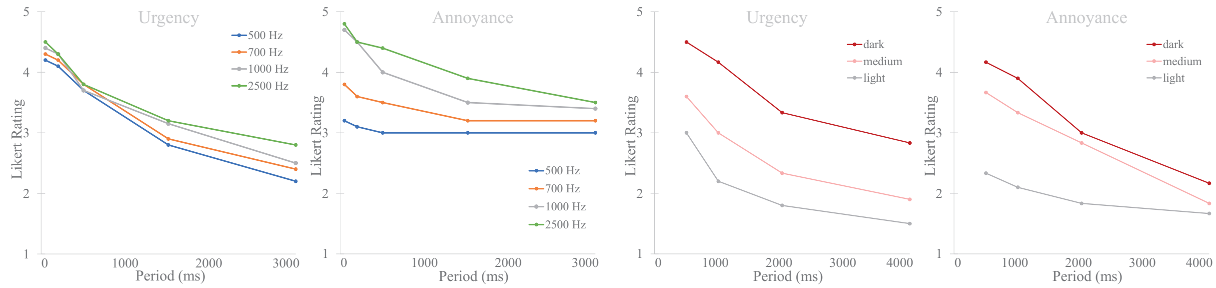
Our platform for this experiment was the mobile base of the iRobot Ava (Fig.2b). The base is holonomic and automatically avoids both static and dynamic obstacles. Two additions were made to the robot for the experiment: 1) a tablet was mounted on a pole above the base for interacting with participants during help requests, and 2) a small pink container was added to the top for holding meal orders.

When requesting help, the robot started playing the help signal as it entered the room. The visual portion of the signal was displayed on the tablet and the sound played from its speakers. The robot always approached the participant with the tablet facing them. After the robot stops at the workstation, the participant touches the tablet on the robot, ending the help signal and displaying the robot's help request. The participant inputs their response on the tablet and the robot drives away. To drop off meal orders, the robot stopped in front of the workstation and waited for the participant to retrieve the batch of meal orders from the pink container.

B. Procedure

As participants entered the experiment room, they were given a brief overview of the study and shown the robot. After obtaining informed consent, a pre-study questionnaire was administered. The experimenter then explained in detail the task that participants were about to perform with the robot and demonstrated how to use the meal order system.

Participants were told that the goal of the study was to better understand how humans and robots can work together. In order to motivate participants to perform the task well, they were also told they could earn a 50% bonus (to their compensation) based on their performance during the task and the overall team performance. Individual performance was defined as the average order input time, average batch input time, and correctness of orders. As we wanted this task to be representative of real world scenarios that involve balancing individual needs with those of the team, partic-



(a) Sound Signals (b) Light Signals

Fig. 3: The results of the participant survey show that signal intensity and period significantly affect participants' ratings of urgency and annoyance for both sound only and light only signals.

ipants were told individual performance affected the bonus more than overall task performance. After assisting the robot, participants rated the help interaction with the robot. At the end of the task, we administered a post-study survey.

C. Manipulated Variables

We manipulated two variables: 1) the *availability* of the human responder and 2) the *urgency* of the robot's help request signal.

Responder availability was manipulated to be either busy or available. The responder was *busy* if the participant was occupied by inputting a batch of meal orders. If the participant was waiting for the robot to drop off new orders, they were *available*. We utilized a human-in-the-loop to identify availability in order to minimize errors. The experimenter utilized a live video stream to send the robot into the room at the appropriate times.

Urgency of the help signal was manipulated to be *low*, *medium*, or *high*. Each help signal consisted of a synchronized light and sound combination that was continuously turned on or off. This resulted in a simple visual signal that flashed between white and *pink* or white and *red* and an audio signal of a sine wave intercut with silence (beeping sound). Red is typically associated with errors, making it a natural color choice for signaling for help.

We chose to use a simple binary signal for several reasons. First, similar signals are already commonly used across a variety of domains and scenarios, including medical alarms, fire alerts, weather alerts, and machine errors [21], [25], [26]. Second, such signals have not been extensively explored in HRI or collaborative robotics, making them potentially valuable tools. Lastly, varying other factors, such as the timing or the shape of the sound wave, would have exponentially increased the number of factors, making the study intractable.

To determine the three levels of help signals, we conducted a survey where participants were exposed to several sound only and light only signals. These signals varied in intensity (i.e., pitch or color) and period. The number of colors tested were limited to those in the pink to red range different enough to be distinctly perceived from a distance. Sound pitch choices were sampled from the range known to be comfortable for human hearing and were selected to be easily differentiable from one another [27]. The period test values were chosen such that change in intensity was perceivable for the smallest period and that the largest period allowed for several cycles to pass during the robot's approach.

A total of 15 participants (8 males, 7 females; ages 23-37, M = 27.67, SD = 3.77) were recruited from the local community. The results of the survey are shown in Fig.3. Participants rated the urgency and annoyance of each of the sound and light signals on a 5-point Likert scale.

A repeated measures ANOVA on the urgency ratings showed a significant effect for sound pitch ($F(3, 297) = 5.09, p = 0.002$) and period ($F(4, 296) = 133.81, p < 0.000$) as well as light intensity ($F(2, 298) = 208.94, p < 0.000$) and period ($F(3, 297) = 121.05, p < 0.000$). Likewise, a repeated measures ANOVA on the annoyance ratings also showed a significant effect for sound pitch ($F(3, 297) = 70.26, p < 0.000$) and period ($F(4, 296) = 25.66, p < 0.000$) as well as light intensity ($F(2, 298) = 147.67, p < 0.000$) and period ($F(3, 297) = 107.82, p < 0.000$).

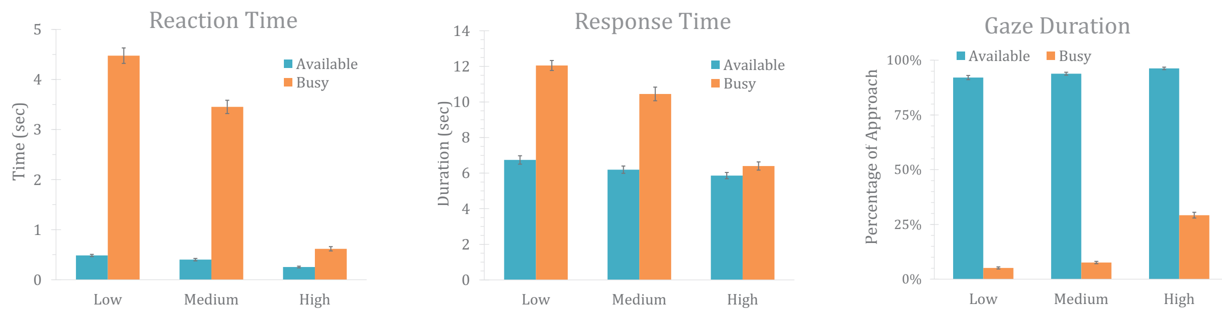
Using these results, we chose three levels of sound pitch and signal period. The low signal consisted of a very light pink color and a 500 Hz sine wave at a period of 3000 ms. The medium signal consisted of a very dark pink color and a 1000 Hz sine wave at a period of 1500 ms. The high signal consisted of a very dark red color and a 2500 Hz sine wave at a period of 250 ms. We restricted the minimum period to be 250 ms as survey participants complained that signals with periods lower than 250 ms were extremely disorienting and uncomfortable to look at.

D. Participants

A total of 30 participants (19 males, 11 females, ages 18-35, M = 25.53, SD =5.42) were recruited from the university. Participants rated their familiarity with robots on a 5-point Likert scale on average 2.63 (SD = 1.06).

The experiment used a within-subjects design that enabled participants to compare the different help request scenarios. Participants were not told that there were different scenarios in order to avoid biasing their reactions to the different signals. The order of the conditions was fully counterbalanced to control for order effects.

To eliminate the novelty effect of the robot, the robot dropped off orders and passed through the experiment room several times before asking for help.



	Reaction Time	Response Time	Gaze Duration
Availability	$F(1,179) = 1228.66, p < 0.000$	$F(1,179) = 251.50, p < 0.000$	$F(1,179) = 15154.62, p < 0.000$
Urgency	$F(2,178) = 300.74, p < 0.000$	$F(2,178) = 81.78, p < 0.000$	$F(2,178) = 183.04, p < 0.000$
Availability,Urgency	$F(5,175) = 238.31, p < 0.000$	$F(5,175) = 46.38, p < 0.000$	$F(5,175) = 100.77, p < 0.000$

Fig. 4: Objective Collaboration Metrics

E. *Dependent Measures*

The dependent measures show the effectiveness of this signaling method for requesting help using both objective and subjective measures as well as the effects of different urgency levels.

The objective measures consisted of *reaction time*, *response time*, and *gaze duration*. The reaction time is the amount of time that passes from when the robot arrives at the workstation with a help request until the participant starts moving to respond to the robot. The response time is the the total amount of time it takes for the participant to respond to the request, starting from when the robot arrives with the help request until the participant completes their response via the tablet interface. The gaze duration is the percentage of the robot's approach, from when it enters the room to when it arrives at the workstation, that the participant's gaze is focused on the robot. Each of these measures were obtained from video data taken from three points in the room, coded by the experimenter.

The subjective measures consisted of 5-point Likert scale ratings of each help interaction for the 1) robot's ability to get the participant's attention, 2) urgency of the robot's request, 3) the participant's annoyance of the help signal, and 4) the overall interaction quality. Urgency and annoyance ratings were used to better understand how people perceive the signals in the context of a collaborative task versus in a vacuum, as in the initial survey. The ability to get people's attention is a common metric for alarms and other signals [13], [21], [26]. Finally, we asked participants to rate the overall interaction.

After the study, we administered a post-study questionnaire and interview asking participants about the task, working with the robot, and the help signals.

V. RESULTS

A. *H1- Design of Nonverbal Signals*

Our first hypothesis looks at whether a simultaneous light and sound signal is effective for indicating a need for help and a level of urgency for that request.

As a manipulation check, we asked participants in the post-study survey to describe the robot's method for requesting help in detail. 100% of participants noticed that the robot used different signals for requesting help. Most participants, however, only mentioned two sets of help signals, urgent and non-urgent. After further probing, we found that only 8 out of 30 (26.67%) participants noticed the difference between low and medium urgency signals during the task, indicating that the manipulation between those signals failed. When participants were shown the signal during the post-study survey, however, all noticed three distinct signals. This suggests that the perceptual difference between low and medium is not large enough that participants can differentiate between the two when concentrating on a different task [28].

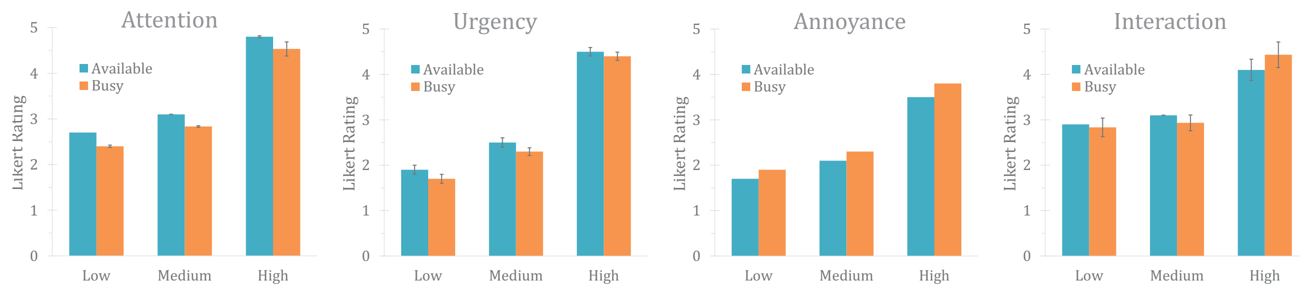
After verifying the manipulation between high and low/medium urgency, we asked participants to interpret the difference between signals. All participants reported that they the different signals represent different levels of urgency.

Participants were also asked whether they used the sound or light more to gauge the urgency of the request. 60% of participants responded that the light, especially its color, was the best indicator of urgency. Only 16.67% of participants chose sound as the better indicator, while 23.3% chose both. Most participants stated the sound got their attention and alerted them to the robot needing help. They could then glance over to the screen and see what color was flashing and determine the urgency of its request.

B. *H2- Objective Collaboration Metrics*

Our second hypotheses examined whether the request scenario affects the time it takes for participants to react and respond to the help request. Repeated measures ANOVAs on participants' reaction time, response time, and gaze duration demonstrate a significant effect for both responder availability and signal urgency, as predicted by *H2*. Furthermore, an interaction effect between availability and urgency was also seen for all three measures. The results of these ANOVAs can be seen in Fig.4, bottom.

Fig.4, left shows a graph of the mean reaction time by condition. As expected, participants reacted much faster when they were *available* with no meal orders to input. Fig.4, middle shows a similar result: participants not only started to move towards the robot faster, but actually completed the help prompt more quickly when they were *busy* inputting



	Attention	Urgency	Annoyance	Interaction
Availability	$F(1,179) = 11.93, p = 0.001$	$F(1,179) = 4.58, p = 0.034$	$F(1,179) = 10.08, p = 0.002$	$F(1,179) = 0.21, p = 0.648$
Urgency	$F(2,178) = 259.24, p < 0.000$	$F(2,178) = 424.38, p < 0.000$	$F(2,178) = 233.85, p < 0.000$	$F(2,178) = 148.63, p < 0.000$
Availability,Urgency	$F(2,178) = 0.02, p = 0.981$	$F(2,178) = 0.18, p = 0.833$	$F(2,178) = 0.21, p = 0.814$	$F(2,178) = 148.63, p = 0.014$

Fig. 5: Subjective Collaboration Metrics

orders. The post-study survey also supported these findings as several participants commented that they attempted to help the robot more quickly when they had remaining meal orders.

We also analyzed participants' gaze behavior and found that when busy, participants rarely glanced at the robot (Fig.4, right), whereas when available, their gaze rarely left the robot. In the post-study survey, participants commented that when available, they wished the robot had moved more quickly as they became impatient waiting for it.

As shown in Fig.4 bottom, the urgency of the signal also significantly affected participants' response. Participants reacted and responded more quickly when the robot used a higher urgency signal. Since most participants grouped the medium and low urgency signals together as not urgent, their reaction times were closer together. The response times showed a similar but less pronounced trend, as it took a certain amount of time to go through the robot's help prompt.

In the post-study survey, participants were asked whether they treated the various help signals differently. 90% of participants said they treated the high urgency signal differently than the other signals. Participants immediately responded to the high urgency signal but waited until finishing at least the current order for the low or medium urgency signals.

Although most participants reported they responded to the low and medium urgency signals the same way, we found that there was a significant difference in their reaction and response times. This stands in contrast to the higher urgency signal in which many participants stated they consciously decided to help the robot immediately, as it seemed better for the task. This suggests that even in this simplified scenario, the factors affecting participants' decisions are complex.

Participants also looked at the robot more, as shown in Fig.4 right, when a higher urgency signal was used. Interestingly, we saw that when busy, participants glanced more often at the robot when it used the high urgency signal (29%) than the lower urgency signals ($5\%, 8\%$). In the post-study survey, participants commented that they kept looking to see how far away the robot was to prepare for its arrival.

C. H3- Subjective Interaction Metrics

Our last hypothesis examined how participants perceive the help interaction based on the request scenario. We asked participants to rate each help interaction for the robot's ability to get their attention, the urgency of the request, the annoyance of the signal, and the quality of the interaction on a 5-point Likert scale. The results are shown in Fig.5 bottom.

Repeated measures ANOVAs showed that responder availability and request urgency significantly affected attention, urgency, and annoyance ratings. For overall ratings of the interaction, only request urgency had a significant effect.

We found in the post-study survey that all participants rated the signals used by the robot were acceptable. However, most participants also suggested changes to the non-urgent signals to make them more discrete and less obtrusive. Participants were most satisfied with the high urgency signal and commented that it made them "react immediately" and would work well in a collaborative task such as this one. Only 3 participants mentioned being bothered that the robot interrupted them while they were busy.

On average, participants rated the collaboration experience with the robot as 4.17 ($SD = 0.52$) and the robot as a partner as 4.17 ($SD = 0.70$) on a 5-point Likert scale. Comments indicated that participants felt they may grow weary of the robot if it were not able to modify its behavior to be more intelligent (e.g., learn to not bother users, learn from its previous help requests).

VI. DISCUSSION

Overall, the findings of our study indicate that nonverbal signals using sound and light can be effective communication tools for non-humanoid robots during collaborative tasks. Although this work only looks at a simple set of signals used during an artificial collaborative task, our findings can be used as a foundation for more complex nonverbal signal design. Furthermore, these results also provide insight into human behavior during collaborative tasks with robots.

During this study, we confirmed that a simple binary sound and light signal can be effectively used to request help during collaboration, with different levels of urgency (H1). We also saw that participants not only reacted faster to a more urgent signal but responded to the request for help quicker as well, confirming H2. This suggests that the designed help signal is an effective medium for conveying the robot's needs to the human collaborator.

We also found that participants only consciously perceived two levels of urgency during the task. Their reaction time, response time, and gaze duration, however, show a clear and significant difference in how they treat each of the three signals. Further complicating these results are many participants' comments indicating that they actively chose to treat urgent and non-urgent signals differently due to the nature of the collaborative tasks. This suggests that participants' reactions to the signals are governed by both conscious and subconscious decision making processes. Hence, further exploration into how humans react to different perceptual phenomena when interacting with a robot can yield essential knowledge for designing robot behavior.

A main goal of this work was to better understand how human users want a robot to behave during collaboration. While we initially assumed participants would be somewhat tolerant of the high urgency signal due to its necessity in critical situation, we were surprised to find that participants were not only tolerant but thought the signal was highly appropriate, despite its annoyance. They found the high urgency signal to be "great at getting their attention" and "good, when used properly." Only two participants said they would change anything about the high urgency signal.

As expected, the low and medium urgency signals were less liked, despite being rated as less annoying than the high urgency signal. While these findings support our notion that the human collaborator's perception of the interaction is affect by the request scenario (H3), we still are limited in our understanding of how these and other factors of the signal will affect the interaction. Hence, this area should be further explored and the request scenario should be further taken into account when designing such signals in the future.

VII. CONCLUSION

This paper explored the design of a nonverbal signals for requesting help and its effects on a human-robot collaborative task. Results suggest that the design of the help-seeking signal is effective at altering human collaborators' responses. However, we also found that people were dissatisfied with the signal's simplicity and thus, we should strive to create more complex signals that take into account human preferences.

Future work will explore creating more complex, expressive nonverbal signals. We will also investigate how to modulate these signals with respect to external factors, such as the environment and collaborative scenario.

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