“Would You Please Buy Me a Coffee?”: How Microcultures Impact People’s Helpful Actions Toward Robots

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ABSTRACT
Robots sometimes face hardware and algorithmic challenges that exceed their capabilities, e.g., an armless robot pressing an elevator button. Previous work suggests that rather than augmenting the robot capabilities, sometimes robots can simply ask for help. A central contribution of this paper is the discovery of how people’s helping behaviors vary within local microcultures, i.e., shared patterns of behaviors and norms linked to local atmospheric conditions and situations. Our methods combine techniques from both social robotics research and ethnography to investigate how people’s helping behaviors toward robots vary across six cafes on a single college campus. We deploy a simple robot to request help ordering items, analyzing the 268 interaction instances to find significant variations in both help and care behaviors toward the robot. Microcultural and situational factors influence this help, motivating the inclusion of cultural criteria into the behavioral predictions of human-robot interaction systems.

Author Keywords
Human-Robot Interaction; Ethnography

CCS Concepts
•**Human-centered computing** → **Human computer interaction (HCI);** Interaction design process and methods;

INTRODUCTION
Robots are leaving the lab and joining our daily life in countless forms, e.g., delivery systems, vacuum cleaners, social companions , and lawnmowers [26, 35, 41, 15]. These robots are capable but limited, coming in a variety of shapes and sizes with distinct sensing and actuation abilities [30], and often benefiting from human assistance [34]. For example, Amazon’s rolling robots have to stay outside until a human picks up the delivered package, and even Ford’s two-legged delivery robots that can walk upstairs may be confounded by the toys on the stairs.

Previous work has demonstrated the value of robot help-seeking as a backdrop for exploring Human-Robot Interaction (HRI) principles [44]. Humans can be of great assistance when robots are facing challenges [3, 10, 2]. Existing studies of help-seeking robots investigate people’s interaction with a robot asking directions [44], a robot asking people to assist its image labeling [37], and a collaborative robot strategically requesting human aid using nonverbal signals [11]. While prior work has focused on optimizing help in a particular application context, this work focuses on a broader research theme: as we deploy robots in complex and varying human environments, what is the role of micoculture in shaping such assistive interactions?

Figure 1: A cafe customer helping the robot buy an item. After placing the item in the basket, he gives the robot a thumbs up as it drives away.

Culture is often assumed as a notion explaining characteristics of certain ethnic groups and countries at a glance. Unlike such a categorical understanding of culture, this paper draws on the anthropological term of culture: shared patterns of behaviors, attitudes, norms and values that help groups adapt to their surroundings [23]. To avoid the confusion between different understandings of culture and to clarify the purpose of this paper, we use and define **microcultures** as shared patterns of behaviors and norms in a social group that is linked to local sets of atmospheric conditions and situations [14, 4].

Drawing upon existing studies that ethnographically reveal the impact of robots on particular communities [35], and impact of context on human attitudes toward robots [38, 26], this paper evaluates the impact of microculture on people’s in-the-wild behaviors toward a robot help seeker. It does so by integrating ethnographic methods into the social robotics design process, combining two distinct onsite study methods: ethnography and in-the-wild user study. Inspired by other roboticists who have

DIS ’20, July 6–10, 2020, Eindhoven, Netherlands.

ACM ISBN 978-1-4503-6974-9/20/07 ...$15.00.
http://dx.doi.org/10.1145/3357236.3395446

used ethnography to gain understandings of how people use or react to robots [19, 26, 35, 38], this paper uses ethnography to explore how robot behavioral designs could benefit from microcultural knowledge.

We primarily focused on how microcultures across a single campus would be different enough to vary people's *likelihood to help*. In particular, we structured our study around the following research questions: **RQ1**: Do (why and when) people help robots?, And **RQ2**: What microcultural and situational factors influence people's help?

Our semi-ethnographic study utilizes a mobile robot in the role of a help-seeker at six cafes that are located in six different buildings on a university campus. A roboticist and a cultural anthropologist collaboratively conducted twelve ethnographic site-visits at those six cafes for eight weeks. We used the ChairBot, a robotics platform that was proven to evoke social responses [22, 1] with minimal nonverbal interaction. We augmented the ChairBot with a small whiteboard that displays its help request, e.g., "Would you please buy me a 16 oz iced americano with this cash?" (featured in Figure 2).

In the course of the study, we also discovered and explored an additional factor, *care*, which we define as instances in which people go beyond help by making sure the robot exits correctly or wishing it well upon its departure. We further teased apart such variations by extracting significant microcultural factors (*social atmosphere, worker attitude, and architecture*) and interaction behaviors (*help and care*) from the collected data. In doing so, this study has come up with a set of correspondences between microcultural/situational factors and help/care behaviors. We think this research approach will be broadly applicable to HRI research especially in investigating the same or similar phenomenon.

RELATED WORK

HRI has made remarkable progress in developing socially intelligent robots that interact with untrained users [8]. This section describes the rising pervasiveness of robots in human settings, the benefits of augmenting traditional user study with ethnography, prior ethnographic results in robotics, and the rationale for focusing our experiments around help.

In recent years, robots provided numerous social services (e.g., delivery systems [26] and emotional supports [35]), while being in hospitals, homes, malls, and many more. Because most HRI typically draws on a psychology-based tradition of in-the-wild studies, fly-on-the-wall observations tend to prioritize participant observations [13]. Nonetheless, if we incorporated participant observations, we would add more opportunities for collecting participant's initial thoughts through instant conversations and co-experiences of interaction situations [13].

Our study combines fly-on-the-wall with participant observations to develop ethnographic theories. As a primary method of anthropology, ethnography investigates the contextual construction of social behaviors and perceptions that are linked to local cultures [20]. Ethnography is known as being relevant in user studies as it helps increase the social adaptability of computational systems [6, 21, 42, 40, 5, 43, 28].

Everyday contexts of robot operation matter because such social and cultural surroundings affect the incidence of desired robot interaction behaviors [24, 26]. Also, HRI researchers are utilizing ethnography to understand human behaviors throughout for in-depth contextual investigation of groups of people [13]. Examples of such studies includes synthetic analysis of distinct stakeholder groups surrounding robotics platforms, investigating robots in roles of home assistants [41, 18], caregivers [35, 31, 39, 27], coworkers [7, 38, 26] and interlocutors [35]. Our study extends this previous recognition of ethnography in HRI with a particular focus on a help-seeking robot and assistive human-robot social interaction.

Once outside the lab, robots might face challenges that exceed their capabilities. HRI researchers demonstrated that robots could reason their abilities and identify when and where to get help [34, 33]. For example, the armless robot (CoBot) was programmed to seek spatially-situated assistance from a nearby human to press an elevator button [34]. In a similar vein, there are studies concerning anti-assistive human behavior, such as protecting robots from children's abuse [9]. While previous work concentrates on algorithmic techniques to seek-help, this research extends that by investigating the microcultural factors that influence people's likelihood to help robots.

Figure 2: The ChairBot with whiteboard, a clipped $5 bill, and a basket asking for help.

ROBOT PLATFORM: *THE CHAIRBOT*

Our study centers around a remotely operated mobile robot that asks people for help with ordering food. The robotic system we deployed is the ChairBot, an established social robot platform [1, 22, 17]. We employed the ChairBot, partially because it was proven to evoke social responses, but also because it blends well into the cafe environments alongside the cafe seating. Immobile, it looks like it belongs. At first, we piloted this study with four ChairBots; however, due to the environmental constraint of the cafes (e.g., narrow paths and crowed hallways), we decided to use a single robot at a time.

The ChairBot is a 9-lb brown-black IKEA STEFAN Chair mounted on top of a Neato Botvac for mobility. The physical design of this robot is covered in [22], and its remote control software is covered in [1]. For this study, we slightly extended the hardware to include a whiteboard, a clip for money, and a basket (Figure 2).

The control infrastructure consists of a laptop and a PS4 controller to drive the robot, a router for an internal network, and two cameras for wizarding and data collection. Most of the data collection occurred via video recordings, for which we have a camera featuring 3840 x 2160 pixels and a 30 Hz frame rate. Another camera is connected to the laptop through which a human operator was wizarding the robot.

Figure 3: The research sites' locations (six cafes) depicted on the map of the campus (sites names are listed in Table1)

ID	Site
C1	Dining Hall Cafe
C2	Engineering School Cafe
C3	Library Cafe
C4	ESL School Cafe
C5	Student Union Cafe
C6	Business School Cafe

Table 1: The study took place in 6 cafes in which we conducted ethnographic site visits. The table lists the visited cafes.

METHODOLOGY

This study is a synthesis of traditional ethnography from anthropology and in-the-wild [32] user studies in HRI. We chose ethnography to provide a holistic view and ensure a prosperous understanding of inhabited cultural factors by observing human behaviors in diverse social settings [43, 28]. Nevertheless, we picked in-the-wild user studies to discover unanticipated aspects of the interactions and improve the design of the ChairBot [45]. Thus, before presenting our results, here, we explain how we approached the study focusing on Research Sites, Data Collection, and Data Analysis in the following subsections.

Research Sites: Six Cafes

We selected six cafes to capture various social climates on campus. We chose buildings that covered a range of pedagogical topics (engineering, English-as-a-second-language, business), and a variety of activities (library, dining hall, student union). The map of research sites is depicted in Figure 3, with a location key and list of trial orders in Table 1. Each cafe features distinct characteristics, as detailed in the Exploration of Cultural Factors Section and Figure 7.

Data Collection

With our university's ethics committee approval, the study aimed to answer the following questions: Why (and when) people help a robot? And, how do microcultures and situations influence instances of help? We formed a multi-disciplinary team of a roboticist and a cultural anthropologist to conduct a set of trials (hereafter referred to as ethnographic *site-visits*) at six cafes over eight weeks (between August and September 2019). Each cafe was visited twice for 12 total visits. All the site-visits have occurred around lunchtime (between 11:00 am and 3:00 pm) and lasted for two hours. Additional to the ethics committee approval, we collected the cafes' managers verbal consent before beginning the site-visits. The data collection subsections cover how we collected the data using two ethnographic methods (Participant and Fly-on-the-Wall Observations), and Video Recordings.

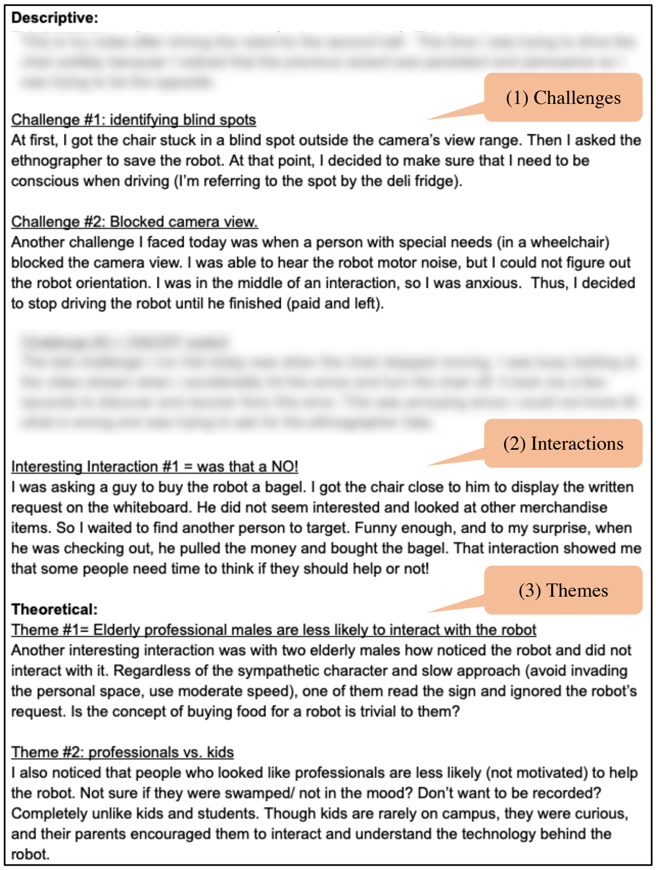
Participant Observations

As an essential data collection technique of ethnography, participant observation allows ethnographers to conduct close-observations and short unstructured conversations(referred to as open-ended interviews in HRI) [25, 29]. In each of our twelve site-visits, a team member played the role of the ethnographer and conducted participant observations. The ethnographer wrote field notes in a shared notebook based on observations and short conversations with participants. To eliminate any bias, half way through the site-visit, the two researchers switched roles allowing both to play the role of the ethnographer in a counterbalanced manner.

At times of "no" interactions, the ethnographer noted participants and cafes' workers behaviors/interactions with the robot. The conversations took place sporadically and were initiated by either the ethnographer or the participant. The ethnographer asked questions regarding the participants' interactions and their perceptions of the robot. When participants initiated conversations, some voluntarily reported their reactions, and others asked about details of the research and technical features of the robot. Meanwhile, conversations with workers took place when the customer flow was slow, or at the beginning and the end of the robot's deployment. Workers talked about their experiences and perceptions of the robot hanging around their workplace and gave the researchers clues on customers' reactions toward the robot. Such unstructured conversations allowed customers and workers to articulate their experience with the robot freely.

Fly-on-the-Wall Observations

In contrast to participant observation, fly-one-the-wall observation minimizes the researcher's intervention to the situation of interaction. While participant observations were taking place, the second team member played the role of the wizard and conducted fly-on-the-wall observations through the webcam from a distance. Because the wizard was operating the robot and simultaneously performing fly-on-the-wall observations, the wizard journaled in a shared notebook, after finishing up each site-visit. The two researchers also counterbalanced between the roles (ethnographer and wizard) by switching after an hour of the site visit.


Descriptive:

Challenge #1: identifying blind spots
At first, I got the chair stuck in a blind spot outside the camera's view range. Then I asked the ethnographer to save the robot. At that point, I decided to make sure that I need to be conscious when driving (I'm referring to the spot by the deli fridge).

Challenge #2: Blocked camera view.
Another challenge I faced today was when a person with special needs (in a wheelchair) blocked the camera view. I was able to hear the robot motor noise, but I could not figure out the robot orientation. I was in the middle of an interaction, so I was anxious. Thus, I decided to stop driving the robot until he finished (paid and left).

Interesting Interaction #1 = was that a NO!
I was asking a guy to buy the robot a bagel. I got the chair close to him to display the written request on the whiteboard. He did not seem interested and looked at other merchandise items. So I waited to find another person to target. Funny enough, and to my surprise, when he was checking out, he pulled the money and bought the bagel. That interaction showed me that some people need time to think if they should help or not!

Theoretical:

Theme #1= Elderly professional males are less likely to interact with the robot
Another interesting interaction was with two elderly males how noticed the robot and did not interact with it. Regardless of the sympathetic character and slow approach (avoid invading the personal space, use moderate speed), one of them read the sign and ignored the robot's request. Is the concept of buying food for a robot is trivial to them?

Theme #2: professionals vs. kids
I also noticed that people who looked like professionals are less likely (not motivated) to help the robot. Not sure if they were swamped/ not in the mood? Don't want to be recorded? Completely unlike kids and students. Though kids are rarely on campus, they were curious, and their parents encouraged them to interact and understand the technology behind the robot.

Figure 4: A sample from an ethnographic journal with callouts to its three major sections.

The wizards' shared journals were in a spontaneous (not technical) language and reflected their methodological reasoning and conclusion. The wizards recorded interesting participants' interactions and initial theoretical themes (step 1 in Figure 4). The wizard also recorded the challenges encountered in moving the robot (i.e., getting the robot stuck in a blind spot). Figure 4 shows a sample of the reflective nature of the journals.

Video Recordings
We collected data via video cameras across all site-visits. The primary video footage was collected with the stationary wireless camera, and the supplementary video footage was collected with the wizarding USB camera. We only coded the video footage from the wireless camera; however, we occasionally referred to the wizarding camera since both cameras offered different angles.

Data Analysis

Unlike the common practice of traditional research approaches, our data analysis process consisted of ethnographic theory-building [29, 12] in conjunction to qualitative data analysis. The combination of both methods allowed us to ensure an adequate understanding of the complex social and technical interactions. This subsection covers each approach in details.

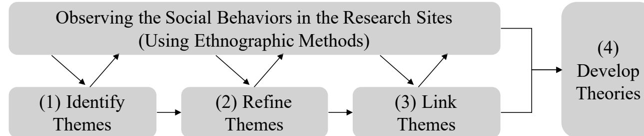


Figure 5: Our ethnographic theory-building process.

Ethnographic Theory Building
To develop the testable theories in this research, we rapidly analyzed the data using four major steps: identify themes, refine themes, link themes and develop theories (Figure 5). The four steps were repeated twice, once with two researchers and once with the whole research team.

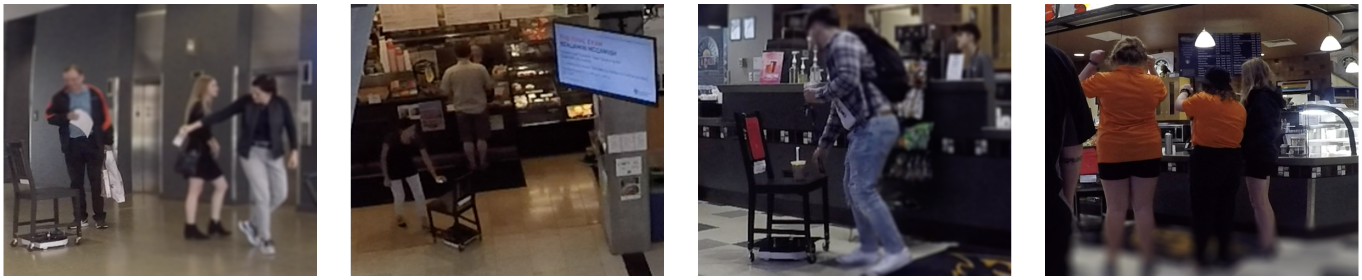
After each visit, two researchers (the first and second authors) examined the collected textual data, manually identified the initial themes, and journaled them in a shared notebook (in depth details and a sample of the ethnographic journals are covered in the Data Collection Subsection). In this process, the two researchers asked each other questions to justify the reasoning behind each theme, refine ailing themes, and link the themes to develop theories that answers the pre-defined research questions (steps 1, 2, 3 and 4 in Figure 5). The two were able to develop 10 theories to propose to the team.

The whole research team had two major meetings to finalize the developed theories. The initial meeting was two weeks into the study, and the research team gathered to identify and refine prominent themes (steps 1 and 2 in Figure 5). At this meeting, the team noticed that some participants took extra measures to help the robot, thus, the researchers started referring to them as caring behaviors. The second meeting was four weeks into the study, and aimed to refine the themes, link the themes and finalize a list of theories (steps 2, 3 and 4 in Figure 5). At this meeting, the team interrupted a set of three microcultural and three situational factors that may predict participants likelihood to help/care for the robot. The team also eliminated any weak themes.

Video Analysis and Inter-Rater Reliability
During the site-visits, the first author conducted video analysis in between trials, which helped develop familiarity with the data and develop expertise in the research sites and behaviors. The researcher segmented the interactions and used three levels of coding, including open, axial, and selective [36].

Open coding was the first phase by which we broke down the video footage into interactions and attached codes to the observed behaviors. To increase the reliability and ensure the subjectivity of the results, the second author has completed an hour of training with the reliability coder (first author). The two researchers independently performed open coding on 20% of the video data and reached > 80% agreement, using MAXQDA (a qualitative and mixed methods analysis software program). Given this reliability, the first author did the rest of the coding individually.

We followed open coding with axial and selective coding. At this step we related the codes to each other using a combination of inductive/deductive reasoning and choose the core



(a) A bystander *helping* without purchasing

(b) A barista *volunteering* to serve without a request

(c) A bystander *adding a straw* to the coffee cup

(d) Bystanders *cheering* for the robot after helping

Figure 6: Four Exemplars of Caring Behaviors

categories/subcategories. This step was essential to develop a single story that answers the developed theories (step 4 in Figure 5). We used inductive reasoning to code the observed caring behaviors and used deductive reasoning to extract the microcultural and situational factors. We thoroughly discuss the derived behaviors and factors in the following sections.

DEVELOPING DEFINITIONS OF HELP AND CARE

We analyzed the data collected from both video recordings and field notes to reveal several predominant interaction behaviors. For example, one of the significant findings was that people frequently cared for the robot beyond the specific request for help. The following subsections share definitions for what we defined as help and care behaviors during our video analysis process. These definitions were grounded in the observation of interactions in the field.

Social Interaction: We define an *interaction* as any encounter the robot has with a person while approaching them with a help request or doing any action to attract their attention. If the targeted person did not look at the robot while its in motion, we considered the encounter as one-sided (not an interaction).

Throughout twelve two-hours trials, we had a total of 268 interactions with cafe customers, and 25% of them yielded on helping instances. 80% of the interactions were with an *individual*, and 20% were with a *group* of two or more individuals. The interactions are by default, initiated by the robot, and aimed to seek help; however, 40% started the interaction by walking toward the robot and interacting with it. The requested food items varied based on the cafes' menus (49% grab and go, 26% drinks, and 25% meals).

Category	Total	Percent
Volunteering Without Request	(37/65)	57%
Anticipating the Robot Needs	(18/65)	28%
Encouraging the robot	(10/65)	15%

Table 2: The researchers elicited three caring behaviors. The categories are listed by number of occurrences descendingly.

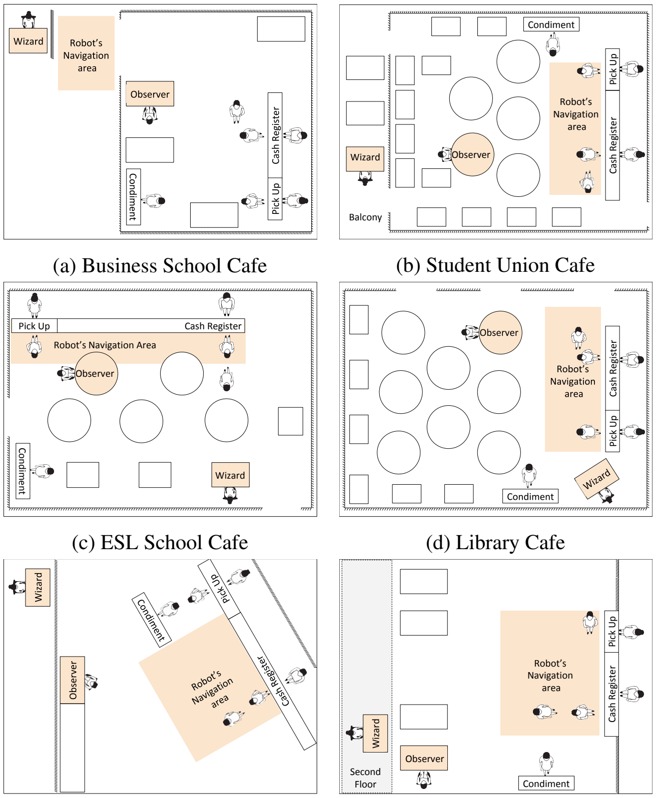
Help: A cafe's customer can decide to *help* the robot by buying the item that the robot is asking for or *not to help* by refusing to purchase the item. We marked an interaction as a help instance if the participant bought the requested item. Refusing to help, however, can be either by ignoring the robot, stopping midway, or using any verbal/non-verbal communication channels to indicate an unwillingness to help. Examples of refusing to interact included saying “NO" or shaking the head, asking someone else to help the robot, staying that they are busy or, in a single extreme case, picking up and moving the robot out of the way.

Care: 60% of participants who helped the robot also *cared* for it by taking further actions beyond “help". We further categorized caring behaviors into three main categories: volunteering without request, anticipating the robot needs, and encouraging the robot with positive statements or gestures (Table 2, Figure 6). A peer reviewed video of these exemplars has been published at [16].

Volunteering services were the most common caring behaviors. The behaviors in this category included: placing and picking up the robot order without buying anything (Figure 6a) and rejoining the order line after leaving the cafe. We also noticed that when a food item was sold out in the ESL school cafe, some participants went to a nearby market to help. Five other participants took the initiative to help when noticing that the current participant is not taking action toward placing an order. Volunteering a service was also seen in the open and semi-open architectures, where the staff left their position behind the register, placed the order, picked it up, and then put it on the chair (Figure 6b).

Considering that most participants were placing orders at a cafe shop themselves, other caring behaviors included order customization (e.g., opting for gourmet option, substituting an ingredient with a healthier one), and picking up complimentary items, (e.g., adding a straw as in Figure 6c), or including napkins and condiments. In an interview with a participant who ordered a hibiscus raspberry tea with frozen berries instead of a standard iced tea, the interviewee stated that she had never had this tea before but opted for it because it sounded flavorful and refreshing. Such behaviors showed that people were willing to go the extra mile to help the robot.

The final category of care included positive gestures and statements of encouragement (Figure 6d). Several participants used a hand gestures such as a thumbs up (Figure 1) or affectionate ones (e.g., patted on the chair) to confirm that they purchased the item and that the robot is ready to go. There were also a few participants who genuinely apologized to the chair itself when placing the wrong order or placing the reminding cash on a different chair.



(a) Business School Cafe (b) Student Union Cafe

(c) ESL School Cafe (d) Library Cafe

(e) Dining Hall Cafe (f) Engineering School Cafe

Figure 7: An abstract illustration of the research sites sorted by their architecture characteristics: Self-Contained (a,b), Semi-Open (c,d), and Open-Space (e,f). The locations of the ethnographer, wizard and the robot are highlighted in orange.

EXTRACTING MICROCULTURAL AND SITUATIONAL FACTORS

In this work, *microcultures* refers to social groups' shared patterns of behaviors and norms, which are linked to local sets of atmospheric conditions and situations. Whereas *situation* refers to a minutely and opportunistically constructed condition of a setting where moment-by-moment social interactions are embedded. Ethnography is well known for its advantage of examining cultures, while in-the-wild user studies are designated to access situations. Thus, we employed ethnography and in-the-wild user study. This section defines and describes the extracted microcultural and situational factors.

Microcultural Factors

A further dive into the deviations at each research site highlighted several microcultural factors. During our exploration of the data, themes such as social atmosphere, worker attitude, and architecture emerged as potential differentiating factors between locations (Table 3). *Social atmosphere* refers to the overall mood of a cafe influencing predominant behavioral norms, such as work, mixed, and playful. *Worker attitude* concerns cafe baristas and cashiers' friendliness towards the robot. *Architecture* concerns the spatial characteristics of a cafe. If the cafe space is open without being barricaded, semi-open, or contained with opaque walls. We describe the six locations with these themes in the subsections below.

The ***Business school cafe*** featured in Figure 7a is located on the first floor of the business school building. It is barricaded with an opaque wall with a single entrance connected to the lobby where a lounge, a stairway, and elevators are located. The cafe occupies a smaller space compared with other semi-open and contained cafes, and has four tables. The customer group of this cafe is usually business students and faculty members. It is worth noting that the cafe manager at this cafe didn't allow the robot to be deployed inside the cafe to avoid crowdedness; thus, we deployed the robot in the lobby area right next to the cafe's entrance.

The ***Student Union cafe*** featured in Figure 7b is located on the second floor of the university's student union building, in which large event rooms, dining facilities, offices, and lounges are clustered. Even though the building is usually crowded, the cafe is contained within opaque walls with a single narrower doorway. A variety of students, faculties, employees, and community members come to this cafe for numerous purposes.

The ***ESL School cafe*** featured in Figure 7c is located on the first floor of a living and learning center for international students. International students attending the university's ESL programs live and study on upstairs floors, where teachers and staff occupy the first floor in the daytime. Within the building, the cafe near a convenience market and residence's kitchen. The cafe area is semi-open with three transparent glass walls, and two open entrances between the glass walls.

The ***Library cafe*** featured in Figure 7d is located on the first floor of the university's main library. It features a semi-open architecture and occupies most of the floor. The cafe is bordered with a narrow barrier and pillars, allowing three access points. The remaining area outside of the cafe hosts three vending machines, restrooms, an elevator, and stairs to the library's main entrance and information desk. The cafe's customers are people who work and study in the library, in addition to customers who drop by to grab beverages and snacks.

The ***Dining Hall cafe*** featured in Figure 7e is located at the left corner of a first-floor food court in a student housing facility. It shares a wide-open hall area with six other food chains and a dine-in area without being barricaded. The cafe is not contained and connected to different stores in a dine-in area where a flow of people pass by. This cafe is located at one of the university's largest dining halls and serves a diverse range of customers coming in for a meal and chilling breaks.

The ***Engineering cafe*** featured in Figure 7f is located at the center corner of a wide-open first-floor atrium in a 153,000-square-foot building. The building's first floor extends up through several floors with a glass roof; thus, the cafe space can be viewed from upstairs and from stairways. There are classrooms, conference rooms, offices and a computer lab near the cafe. There also is a spacious lounge area facing the cafe.

Situational Factors

Further examination into the context of use highlighted several situational factors. During our exploration of the data, themes such as the type of the food item, the robot approaching style, and the number of people in an interaction emerged as potential differentiating factors (Table 3). We describe the three factors in the subsections below.

1: Microcultural Factors		
Factor	**Category**	**Sub Categories**
Social Atmosphere	Work Mood	Business School Cafe
	Mixed	Library Cafe
		Engineering School Cafe
		Student Union Cafe
	Playful	Dining Hall Cafe
		ESL School Cafe
Worker Attitude	Friendly	Engineering School Cafe (Visit#1)
		Dining Hall Cafe (Visit#1)
		ESL School Cafe (Visit#1)
	Neutral	Library Cafe (Visit#1)
		Dining Hall Cafe (Visit#2)
		ESL School Cafe (Visit#2)
		Student Union Cafe (Visit#1)
		Engineering School Cafe (Visit#2)
		Business School Cafe (Visit#2)
	Unfriendly	Business School Cafe (Visit#1)
		Student Union Cafe (Visit#2)
		Library Cafe (Visit#2)
Architecture	Self-Contained	Business School Cafe
		Student Union Cafe
	Semi-Open	ESL School Cafe
		Library Cafe
	Open Space	Dining Hall Cafe
		Engineering School Cafe
2: Situational Factors		
Factor	**Category**	**Sub Categories**
Food Items	Grab and Go	Bakery Items (Muffin, Twist, and croissant)
		pre-packaged foods (Chips, Hummus, and Banana)
	Drink Orders	Coffee, Tea, and Smoothie
	Meal Orders	Grilled Sandwiches, Crapes and Wrap
Robot Approaching Style	Pushy	Wizard with ethnography background
	Subtle	Wizard with robotics background
Number of people	Individual	Single
	Group	Two or more

Table 3: The Microcultural and Situational Factors were elicited and its corresponding categories.

Food Items: The first situational factor that emerged from the data analysis was the impact of the requested food item on people's likelihood to help the robot. The cafes offered similar menu items (e.g., coffee, tea, pastries, sandwiches, chips, etc.) Thus, food items the robot ordered varied from one cafe to another. We tracked these food items and categorized them as Grab and Go, Drink Order, and Meal Order. Grab and go orders refer to food items that require no preparation time such as bakery items like muffins or croissants and ready to go foods such as chips, hummus, or a banana. Drink orders refer to liquid items that require some preparation time, such as coffee, tea, and smoothies. Finally, meal orders refer to advanced food items that require preparation for a longer time, such as grilled sandwiches, crepes, and wraps. The distribution of the three requested food items categories was 49% for grab and go orders, 26% for drinks, and 25% for meal orders.

Robot Approaching Style: The second situational factor that emerged from the data analysis was the impact of robot approaching style on people's likelihood to help the robot. Though we did not initially plan to introduce distinguished robot approaching styles, both wizards had a different operating style that influenced the robot's perceived character. Thus, we identified the two approaching styles (Pushy and Subtle) by the sequences of actions an operator took to recruit a bystander. The pushy style addressed a bystander and repeated the help request at least twice. If the participant pulled out the clipped cash, the robot spins in a happy-like dance. The subtle style, on the other hand, addressed a bystander and repeated the help request at maximum twice. If the bystander pulled the clipped cash, the robot walked to the register next to the bystander. Interestingly, because the two researchers alternated roles, we have a close to even distribution of both approaching styles (53% subtle and 47% pushy).

Number of People: The third situational factor that emerged from our data analysis was the impact of the number of people in the interaction on people's likelihood to help the robot. The real-world nature of the study did not exclude anyone from interacting with the robot. Thus we identified two categories for this factor (Individuals vs. Groups). 80% of the interaction instances were with individuals, and the reminder 20% were with a group of two or more people.

RESULTS 1: WHY PEOPLE HELPED THE ROBOT

This first results section uses ethnographic analysis to understand some of the reasons why people helped the robot, and their understanding of that situation. Our participant observations revealed that people helped the robot for five reasons: (1)Amusement, (2)Curiosity, (3)Ethical Basis, (4)Academic Dedication, and (5)Revenue Increase. Though we could not interview every participant, we were able to raise enough ethnographical evidences behind the help behaviors.

First, people helped the robot **seeking a sense of amusement**. Regardless of the novelty effect, people were amused by their interaction with the ChairBot. At the engineering school cafe -where the cafe and building employees are already familiar with the ChairBot and have interacted with the ChairBot multiple times- the cafe manager introduced the robot to the customers as a "regular customer" and encouraged clients to interact with it. This entertainment climate expanded the instance of help and encouraged those who are hesitant to take a step. As if running into a friend, an engineering school employee greeted the robot with a big smile, saying: "Oh, you are here again! What can I do for you? [after reading the request on the whiteboard] Haha, I see. I'd love to buy you a coffee!" The employee told another cafe customer, "This little guy gave me a candy last Halloween, and this time it is asking me to buy a coffee, haha, how fun!"

Second, people helped the robot to **satisfy a sense of curiosity**. A chair robot does not need food; as such, people wanted to see the robot's reaction when they helped. Parents who accompanied their freshmen showed a liberal curiosity by encouraging their kids to help the robot and asked: "Do you want to help the robot? How do you think it works?" Students were also curious about how the robot worked. In one instance, two students tested the robot's perception and path planning by moving around the robot, then went to the researcher asking technical questions "Dose the robot see people or has object detection functionalities? How the robot realize if it has received food?" After the researcher answered their questions (Robot Platform section), they decided to experience the robot's reaction by offering help.

Third, people helped the robot because of their **desires to be ethical**. Ethical behaviors were divided into two levels: Good Samaritan and Honest John. From our conversations, people described a desire to help the person who sent the robot out to the cafe rather than to help the robot itself; this explains what we refer to as Good Samaritan. For example, a participant in the library's cafe stated that he thought that a person with a disability sent the robot to get him/her a coffee. Likewise, a student who was going through his mid-term said: "I imagined that a student who is preparing a mid-term had sent the robot to the cafe to buy food. I wanted to help the busy student." Honest John refers to how some particpants perceived the robot as an innocent agent that may be easily deceived. A customer who helped the robot said: "I thought that this is a research study testing people's ethical behaviors. In other words, would people steal the money from a vulnerable robot."

Fourth, people helped the robot based on their desires to make **academic dedication**, associated with their mental model of supporting the university students. A participant said: "As a university employee, I always think that my priority is to support students' work. I helped the robot because it was obvious that it is research run by students in this school, and I'm willing to help the research occurring in our academic community." Similarly, a participant came to the researcher after offering help to the robot and stated that: "I didn't help the robot but you, a researcher who is running this study. I also do my own experiments as a graduate student, and I know how hard it is. If I didn't notice you, I wouldn't help the robot."

Finally, some cafe staff helped the robot to promote their business. The cafe manager at the library said she wanted to help the robot as long as it garners customers' attention and increases revenues. The manager at the dining hall said that he wanted to have the robot in as long as it **increases revenue** and brings joy. A staff member followed his comment: "Oh you are talking about Charles, we call him Charlie the chair here. Look at our customers enjoying watching the robot. I think this little one is helping develop a good mood in this cafe, and I wanted it to get help to keep amusing people."

RESULTS 2: FACTORS PREDICTING HELP AND CARE

To answer the question of whether microcultural and situational factors would influence the results, we ran the following analyses: (1) Is there a significant differences between cafe microcultures and its factors on the likelihood to help/care? (2) Is there a significant differences between food items (grab&go, drink, or meal) on the likelihood to help/care? (3) Is there a significant differences between the robot's approaching styles (subtle vs. pushy) on the likelihood to help/care? And (4) Is there a significant differences between the number of people in a given interaction (individual vs. group) on the likelihood to help/care? We hypothesized these questions from our ethnographic journey to user studies.

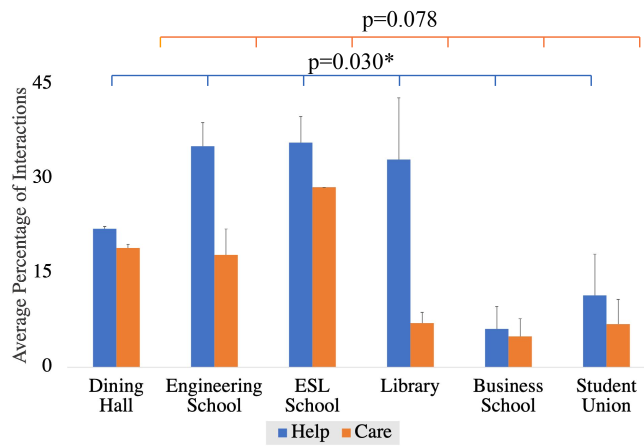
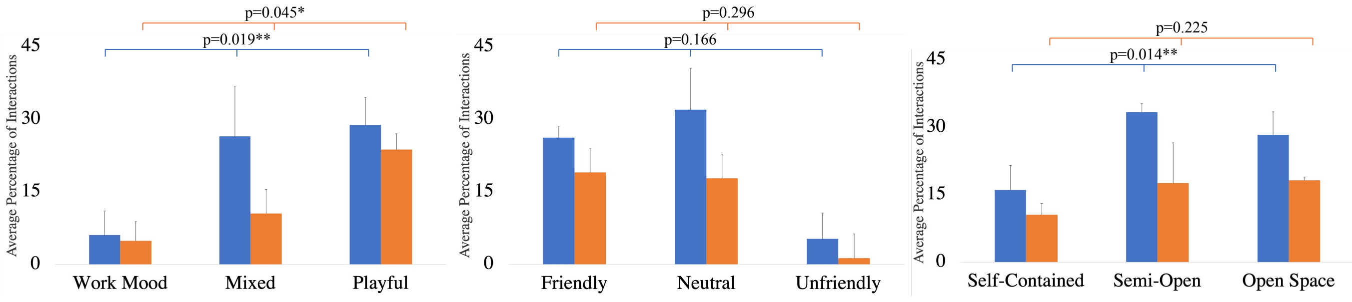


Figure 8: Location was a significant different across help but not care. These results are further teased apart in Figure.9

Cafe microcultures and its factors

Cafe microculture was a significantly different for help (ANOVA, F=2.85 ,df=(5,262), **p= 0.030***) but not care (ANOVA, F=2.85, df=(5,262), p= 0.078). People in some areas had different attitudes toward the robot wandering around their cafe environments. They also had different understandings of how they should treat the robot. For example, the business school and student union had the lowest frequency of both help and care(Figure 8). Whereas, those in the engineering school, library building, and ESL building were highly likely to help the robots. In some locations, help and care seemed to go hand in hand while in others, like the Library, people seemed to have quite different values. We tried to further understand such differentiation by analyzing cultural factors that emerged in the course of our research process (Methodology Section). Those microcultural factors include: Social Atmosphere, Worker Attitudes, and Architecture.

Social Atmosphere: Social atmosphere was significantly different in whether people would help the robot (ANOVA, F=2.5 ,df=(2,265), **p= 0.019****). People were most likely to help the



(a) Social Atmosphere (b) Worker Attitude (c) Architecture

Figure 9: *Cultures Factors:* (a) Social Atmosphere was significant for help and care, (b) Workers attitude did not significantly impact help or care, but numerically, unfriendly attitudes reduced both, (c) Architecture was significant for help but not care.

robot in playful and mixed mood atmospheres (Figure 9a). In the ESL school where international students live and study, a lot of students seemed to enjoy their summer study abroad time. The robot's presence often worked as a special event for them, especially during our first visit. Some even initiated interaction even before the study began, and they wanted to take videos and pictures of the robot. A student told the robot, "Hey girl, [after reading the sign] Ok, come on, I will buy you a muffin! Can you follow me? Wow, you can follow me."

Social atmosphere similarly was significantly different in whether people would care (ANOVA, F=2.5, df=(2,265), **p=0.045***). In this case, the directionality was similar. The playful atmosphere received the most frequent instances of care (Figure 9a); for instance, in the dining hall, three of the interactions were made by participants who had rejoined the physical area where the robot was wandering. One student said,"Oh, no one wants to buy a tea for you? I'll do it for you." In addition, there was a woman who passed by the robot at first. However, after noticing that no one was offering help, she voluntarily came back, saying, "Okay, I will buy you the chips, but you should go for a healthier option next time, okay?"

Worker Attitude: A higher number of people showed caring behaviors toward the robot when the cafe worker attitudes toward the robot were positive (Figure 9b). However, this result was not statistically significant (ANOVA, F=3.75, df=(2,265), p=0.166). Help was also numerically more common in cases when worker attitude was positive, which was not shown in a statistical trend (ANOVA, F=3.75, df=(2,265), p=0.296). Based on the observations and numerical data during the two library visits, however, we infer that this theory would be interesting to explore further in a more controlled setting.

Architecture: Cafe's architecture was significantly different for whether people would help (ANOVA, F=2.21, df=(2,265), **p=0.014****) but not care (ANOVA, F=2.21, df=(2,265), p=0.255). Overall, people were most likely to help the robot in the open and semi-open conditions (Figure 9c). We infer that it is because open-spaced areas were more likely to be linked with the uplifting mood in general while people were more likely to be quite and self-engaged in their work or group conversations at self-contained cafes. Contrarily, in self-contained areas, interactions easily garnered others' attention, so, many people did not want the attention by interacting with the robot.

Food Items

People were more likely to help the robot by buying food when the order had less waiting time (Figure 10a). Item type significantly impacted the likelihood of help (ANOVA, F=2.30, df=(1,266), **p=0.001****). People were most likely to help the robot for the grab and go food items that require a short time investment, followed by a drink, then meal orders. While participants did not explicitly comment on the item types, we believe the wait time influenced their likelihood to help.

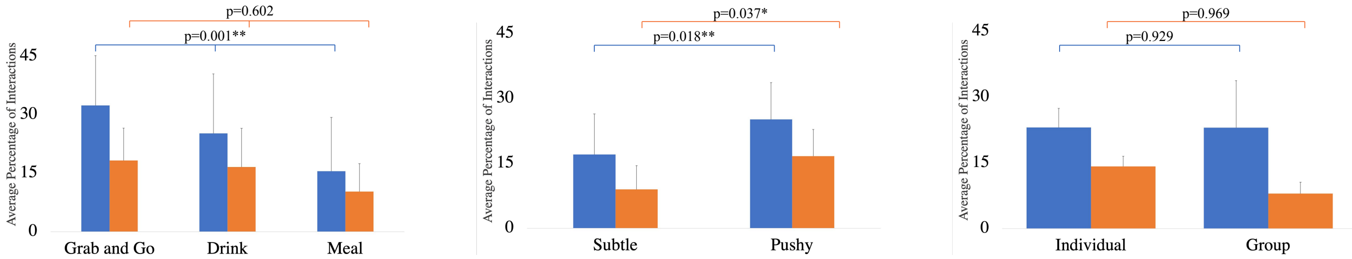
As Figure 10a shows, care was not significantly different (ANOVA, F=1.42, df=(1,266), p=0.602). Meaning, the level of wait time did not influence their likelihood to make an extra effort to take care of the robot. For example, regardless of the food item type, participants offered napkins for messy food items such as grilled cheese sandwiches (meal, high effort) and muffins (grab & go, low effort). Whereas, for chips and bananas, which were grab and go items, people didn't pick up napkins with them. Also, for iced coffees and teas (drink, moderate effort), people often offered straws and cup holders along with them.

Robot's Approaching Styles

The two Robot's approaching styles were significantly different for help (ANOVA, F= 4.29, df=(1,266), **p=0.018****) and care (ANOVA, F=4.29, df=(1,266), **p=0.037***). The pushy robot demonstrated higher means of help and care, as compared to the more subtle robot. As Figure 10b shows, people were most likely to help the robot when it consistently asked them for help. Participants also cared for the pushy robot more than the subtle one by customizing the order to include healthier options such as ordering a crepe without cream. Even participants who did not help the robot expressed a sense of care saying, "Sorry, I'm in a hurry." Patting was another common behavior that more frequently happened for the pushy robot. The pushy robot easily an uplifting mood, for instance one participants said: "Turn around if you want a muffin!"

Number of People

Numerically, a higher number of people showed caring behaviors toward the robot when they were by themselves com-



(a) Food Items (b) Robot Approaching Style (c) Number of People

Figure 10: *Situational Factors:* (a) Food items were significant for help but not care, (b) Robot approaching style was significant for help and care, (c) Number of people in an interaction did not impact help nor care.

pared to when in a group of two or more people (Figure 10c). However, this result was not statistically significant (ANOVA, F=0.009, df=(1,266) , p=0.969). Help also was not statistical significant (ANOVA, F=3.75, df=(2,265), p=0.296). Based on the observations and numerical data, however, we infer that this theory would be interesting to explore further by collecting data about behaviors and psychological processes occurring within groups.

DISCUSSION

Mixing Microcultural investigations with in-the-wild user studies is an under explored approach in human-robot interaction and robotics behavioral design. In this work, we extend the current literature on help-seeking by:

- Creating microcultural and situational insights into social robot behavior design.
- Highlighting the importance of behavior design in the successful integration of social robotics platforms.
- Suggesting a methodological incorporation within HRI research for future investigations of a similar phenomenon.

It was not always easy to mesh up ethnographic methods with in-the-wild user studies. The roboticist had to treasure the validity of ethnographic theory-building and be flexible as the study progressed. The definition of microculture we applied in this study was complex as an anthropological and ethnographic concept: local subcultures comprising different values, norms, and attitudes that are internalized by different groups of people around the cafes [14, 4]. Drawing on the established notion of microculture, we investigated ways in which locations (cafes), even in a single united local community (a university campus), would be associated with distinct socio-cultural dynamics.

This study supports the idea that ethnography is well suited to in-the-wild HRI research experimentation where human behaviors can not be pre-defined. The process also came up with significant situational factors. Those factors would not be generated as proper study manipulations if we had not given up over-controlling the experimental design. We showed how ethnographic concepts and approaches might give insights into human-robot social interaction.

In terms of future work, we remain highly interested in the influence of workers' attitude on people's help and care behaviors. While we could not show statistical significance, we still strongly infer the impact of cafe workers' attitudes from our experience at the library's cafe. Ethnographic incidents draw on ethnographers' reflection and often serve as valid evidence by themselves. In other words, much can be learned from nominal examples of activity, even though a similar breadth of worker attitudes were not seen in other cafe locations. Hence, we suggest a more embracing understanding of ethnographic and qualitative styles of data analysis in the field, and more excellent representation and integration into the future development of culturally-adaptable social robots.

CONCLUSION

This paper presents a semi-ethnographic study exploring the impact of microcultures on the likelihood of people to help a robot. The ChairBots attempted to order foods at six cafes on a college campus in order to surface local cultural variants. Our final dataset included 268 interaction instances, which we analyzed to answer our initial research questions, first ethnographically, then statistically.

RQ1: People do help the robots, but the whys vary. Many people helped the robot seeking amusement and because they were curious what it was doing or how it worked. Other reasons for assisting the robot included a hidden desire to help the vulnerable robot and the researchers behind its deployment. In a few cases, cafe's workers helped the robot to market their business and increase revenue.

RQ2: Microculture does vary people's likelihood to help and express care to the robot. In terms of principles that future robot designers could use in designing robots asking for help, we found that robots should: (1) be assertive about asking for help, e.g., via driving style, as they need to motivate bystanders, (2) ask for easier instances of help, i.e., simple items that have lower time investments, and (3) seek help where people are taking a break or have casual attitudes, rather than people tunneling into work or meetings.

These results demonstrate the potential for ethnographic approaches to elicit real-world microcultural factors that will make social robotic systems more successful, as many of our final analysis variables were sourced in the wild. We hope others continue to use interdisciplinary methodologies to source robust concepts and implementation ideas for future robots. In inverting the results of this paper, future work might also consider the concept of a robot bystander that offers care to people. True help, based on these human results, is not merely literal but involves anticipating the needs of others.

REFERENCES

[1] Abhijeet Agnihotri and Heather Knight. 2019. Persuasive ChairBots: A (Mostly) Robot-Recruited Experiment. In *Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI '19)*. IEEE, Daegu, Korea.

[2] Nils Backhaus, Patricia H Rosen, Andrea Scheidig, Horst-Michael Gross, and Sascha Wischniewski. 2018. Somebody Help Me, Please?!" Interaction Design Framework for Needy Mobile Service Robots. In *Proceedings of IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO '18)*. IEEE, Genoa, Italy, 54–61.

[3] Markus Bajones, Astrid Weiss, and Markus Vincze. 2016. Help, Anyone? A User Study for Modeling Robotic Behavior to Mitigate Malfunctions With The Help of The User. *arXiv preprint arXiv:1606.02547* 1, AISB-NFHRI/2016/02 (2016).

[4] Roberts Keith A. Ballantine, Jeanne H. and Kathleen Odell Korgen. 2011. *Our Social World: Condensed: An Introduction to Sociology*. Milton, Queensland: John Wiley & Sons, Thousand Oaks, CA, United State. 72 and 93 pages.

[5] H Russell Bernard. 2017. *Research methods in anthropology: Qualitative and quantitative approaches*. Rowman & Littlefield, Lanham, MD, United State.

[6] Lasse Blond. 2019. Studying robots outside the lab: HRI as ethnography. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 117–127.

[7] Leon Bodenhagen, Kerstin Fischer, Trine S Winther, Rosalyn M Langedijk, and Mette M Skjøth. 2019. Robot use cases for real needs: A large-scale ethnographic case study. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 193–206.

[8] Cynthia Breazeal. 2009. Role of expressive behaviour for robots that learn from people. *Philosophical Transactions of the Royal Society B: Biological Sciences* 364, 1535 (2009), 3527–3538.

[9] Drazen Brscić, Hiroyuki Kidokoro, Yoshitaka Suehiro, and Takayuki Kanda. 2015. Escaping From Children's Abuse of Social Robots. In *Proceedings of the 10th annual ACM/IEEE International Conference on Human-Robot Interaction(HRI '15)*. ACM, Portland, United State, 59–66.

[10] David Cameron, Ee Jing Loh, Adriel Chua, Emily Collins, Jonathan M Aitken, and James Law. 2016. Robot-Stated Limitations But Not Intentions Promote User Assistance. *arXiv preprint arXiv:1606.02603* 1, AISB-NFHRI/2016/07 (2016).

[11] Elizabeth Cha and Maja Matarić. 2016. Using nonverbal signals to request help during human-robot collaboration. In *Proceedings of the 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '16)*. IEEE, Daejeon, Korea, 5070–5076.

[12] Kathy Charmaz. 2014. Constructing grounded theory (Introducing qualitative methods series). (2014).

[13] Bohkyung Chun and Heather Knight. 2020. The Robot Makers: An Ethnography of Anthropomorphism at a Robotics Company. *ACM Transactions on Human-Robot Interaction (THRI '20)* (2020).

[14] Dermot Crowley. 2018. *Smart Teams: How to Work Better Together*. Milton, Queensland: John Wiley & Sons, Thousand Oaks, CA, United State. 154 pages.

[15] Paul Dumouchel. 2017. *Living with robots*. Harvard University Press, Boston, United States.

[16] Abrar Fallatah, Bohkyung Chun, Sogol Balali, and Heather Knight. 2020. Semi-Ethnographic Study on Human Responses to a Help-Seeker Robot. In *Proceedings of the 15th ACM/IEEE International Conference on Human-Robot Interaction (HRI '2020)*. 640–640.

[17] Abrar Fallatah, Jeremy Urann, and Heather Knight. 2019. The Robot Show Must Go On: Effective Responses to Robot Failures. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '2019)*. IEEE, Macao, China.

[18] Julia Fink, Valérie Bauwens, Omar Mubin, Frédéric Kaplan, and Pierre Dillenbourg. 2011. *HRI in the Home: A Longitudinal Ethnographic Study with Roomba*. Technical Report. NCCR robotics.

[19] Jodi Forlizzi. 2007. How robotic products become social products: an ethnographic study of cleaning in the home. In *Proceedings of the ACM/IEEE international conference on Human-robot interaction*. ACM, Washington DC, United States, 129–136.

[20] Martyn Hammersley. 2018. What is ethnography? Can it survive? Should it? *Ethnography and Education* 13, 1 (2018), 1–17.

[21] Cathrine Hasse, Stine Trentemøller, and Jessica Sorenson. 2019. Special Issue on Ethnography in Human-Robot Interaction Research. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 180–181.

[22] Heather Knight, Timothy Lee, Brittany Hallawell, and Wendy Ju. 2017. I Get It Already! The Influence of ChairBot Motion Gestures on Bystander Response. In *Proceedings of the 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN '17)*. IEEE, Lisbon, Portugal.

[23] Robert H Lavenda and Emily Ann Schultz. 2010. *Core concepts in cultural anthropology*. McGraw-Hill, New York, NY, United State.

[24] Min Kyung Lee, Sara Kiesler, Jodi Forlizzi, Siddhartha Srinivasa, and Paul Rybski. 2010. Gracefully Mitigating Breakdowns in Robotic Services. In *Proceedings of the 5th ACM/IEEE international conference on Human-robot interaction (HRI '10)*. IEEE, Osaka, Japan, 203–210. DOI: http://dx.doi.org/10.1109/HRI.2010.5453195

[25] Kathleen Musante and Billie R DeWalt. 2010. *Participant observation: A guide for fieldworkers*. Rowman Altamira, Lanham, MD, United States.

[26] Bilge Mutlu and Jodi Forlizzi. 2008. Robots in Organizations: The Role of Workflow, Social, and Environmental Factors in Human-Robot Interaction. In *Proceedings of the 3rd ACM/IEEE international conference on Human Robot Interaction(HRI '08)*. IEEE, Amsterdam, The Netherlands, 287–294. DOI: http://dx.doi.org/10.1145/1349822.1349860

[27] Niels Christian Mossfeldt Nickelsen. 2019. Imagining and tinkering with assistive robotics in care for the disabled. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 128–139.

[28] K. O'Reilly. 2012. *Ethnographic Methods*. Taylor & Francis, Milton Park, Abingdon, UK. https://books.google.com/books?id=ncCLAgAAQBAJ

[29] Andreas F Phelps and Michael J Horman. 2010. Ethnographic theory-building research in construction. *Journal of construction engineering and management* 136, 1 (2010), 58–65.

[30] Francesco Riccio, Andrea Vanzo, Valeria Mirabella, Tiziana Catarci, and Daniele Nardi. 2016. Enabling Symbiotic Autonomy in Short-Term Interactions: A User Study. In *Proceedings of the International Conference on Social Robotics (ICSR '16)*. Springer, Kansas City, United States, 796–807.

[31] Kathleen Richardson. 2018. *Challenging Sociality: An Anthropology of Robots, Autism, and Attachment*. Springer, Berlin, Germany.

[32] Raquel Ros, Marco Nalin, Rachel Wood, Paul Baxter, Rosemarijn Looije, Yannis Demiris, Tony Belpaeme, Alessio Giusti, and Clara Pozzi. 2011. Child-robot interaction in the wild: advice to the aspiring experimenter. In *Proceedings of the 13th international conference on multimodal interfaces (ICMI '11*. ACM, Alicante, Spain, 335–342.

[33] Eric Rose. 2016. Approaching Humans For Help: A Study of Human-Robot Proxemics. Union College Honors Thesis. (2016).

[34] Stephanie Rosenthal and Manuela Veloso. 2012. Mobile Robot Planning to Seek Help With Spatially-Situated Tasks. In *Proceedings of the Twenty-Sixth AAAI Conference on Artificial Intelligence*. AAAI, Toronto, Canada.

[35] Alessandra Maria Sabelli, Takayuki Kanda, and Norihiro Hagita. 2011. A Conversational Robot in an Elderly Care Center: An Ethnographic Study. In *Proceedings of the 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI '11)*. IEEE, Lausanne, Switzerland, 37–44.

[36] Johnny Saldaña. 2015. *The coding manual for qualitative researchers*. Sage, Thousand Oaks, CA, United State.

[37] Elaheh Sanoubari and James E Young. 2018. Hi Human Can We Talk? An in-the-wild Study Template for Robots Approaching Unsuspecting Participants. In *Workshop on the Social Robots in the Wild at the International Conference on Human-Robot Interaction (HRI '18)*. ACM/IEEE, Chicago, United State.

[38] Allison Sauppé and Bilge Mutlu. 2015. The Social Impact of a Robot Co-worker in Industrial Settings. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*. ACM, Seoul, Korea, 3613–3622.

[39] Hyunsoo Song, Min Joong Kim, Sang-Hoon Jeong, Hyen-Jeong Suk, and Dong-Soo Kwon. 2009. Design of Idle Motions for Service Robot via Video Ethnography. In *Proceedings of the 18th IEEE International Symposium on Robot and Human Interactive Communication(RO-MAN '09)*. IEEE, Toyama, Japan, 195–199.

[40] Jessica Sorenson. 2019. Toward a pragmatic and social engineering ethics. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 207–218.

[41] Ja-Young Sung, Rebecca E Grinter, Henrik I Christensen, and Lan Guo. 2008. Housewives or Technophiles?: Understanding Domestic Robot Owners. In *Proceedings of the 3rd ACM/IEEE International Conference on Human-Robot Interaction (HRI '08)*. IEEE, Amsterdam, The Netherlands, 129–136.

[42] Jamie Wallace. 2019. Ethics and inscription in social robot design. A visual ethnography. *Paladyn, Journal of Behavioral Robotics* 10, 1 (2019), 66–76.

[43] Christina Wasson, Mary Odell Butler, and Jacqueline Copeland-Carson. 2016. *Applying anthropology in the global village*. Routledge, London, United Kingdom, England.

[44] Astrid Weiss, Judith Igelsböck, Manfred Tscheligi, Andrea Bauer, Kolja Kühnlenz, Dirk Wollherr, and Martin Buss. 2010. Robots Asking for Directions: The Willingness of Passers-by to Support Robots. In *Proceedings of the 5th ACM/IEEE international conference on Human-Robot Interaction (HRI '10)*. IEEE, Osaka, Japan, 23–30. DOI: http://dx.doi.org/10.1109/HRI.2010.5453273

[45] Stephen Yang, Brian Ka-Jun Mok, David Sirkin, Hillary Page Ive, Rohan Maheshwari, Kerstin Fischer, and Wendy Ju. 2015. Experiences developing socially acceptable interactions for a robotic trash barrel. In *Proceedings of the 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN '15)*. IEEE, Kobe, Japan, 277–284.