Should I Help?: A Skill-Based Framework for Deciding Socially Appropriate Assistance in Human-Robot Interactions

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***Abstract*— As robots are increasingly integrated into various aspects of everyday life, it becomes essential to develop intelligent systems capable of providing assistance while maintaining social appropriateness. In this paper, we challenge the prevailing assumption that robots should always offer help, prompting an essential discussion of when robots should offer help. We present a systematic way of considering socially appropriate assistance in human-robot interaction and introduce a theoretical framework that enables robots to discern whether or not to offer help to a human user. We examine the factors that influence the social appropriateness of help, including the relative skill levels between the robot and user and measures for assessing the social value and cost of help. Through a series of illustrative examples, we demonstrate the feasibility of our framework in providing socially appropriate assistance.**

I. Introduction

Helping is a fundamental human relationship: parents nurture their children, healthcare providers extend care beyond medical treatment amidst a global pandemic [1], online communities emerge as a nexus of mutual aid [2], [3], and friends lend a listening ear during difficult moments. Even the everyday experiences of holding a door open or giving up one's seat on public transportation for someone in need underscore helping as a fundamental human dynamic.

Yet, people do not always welcome offers of help. What goes on and what goes wrong when one attempts to assist a friend and is rudely rebuffed [4], [5]? How is it possible that a helping hand is overbearing when regarding a colleague's work, yet highly appreciated when it eases a personal struggle? While helping is pervasive in our daily lives, the act of offering help can sometimes be met with resistance. It has been said that we take helping so much for granted in our ordinary, daily life that the word "help" itself comes up only when someone is said to have "not been helpful" [4].

Robots are built to assist people. As robots assume increasingly diverse roles ranging from home assistance [6] and healthcare [7] to education [8] and entertainment [9], the need to imbue these machines with a nuanced understanding of socially appropriate assistance becomes imperative [10]. The ability to discern whether it is appropriate to offer assistance extends beyond mere functional efficiency. It has the potential to cultivate trust, foster rapport, and adhere to intricate societal norms [11], [12]. Robots that possess the acumen to anticipate user needs, adapt to situational cues, and offer support in a socially appropriate manner become valuable partners in human activities.

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Fig. 1: A social robot contemplates the appropriateness of offering assistance to its human user, taking into account factors such as relative skill, cost, and utility of help.

The concept of help has traditionally encompassed a broad spectrum of mutual understanding and actions. Moreover, an offer of help can take various forms, from explicit requests to nonverbal cues and gestures. For the scope of our investigation, we define *help* as an optional contribution that makes a specific, solvable task easier for a human, as determined by an appropriate measure such as time or effort. Following this, *socially appropriate help* can be defined as the capacity to discern when and how to extend assistance that aligns with human expectations, social norms, and nuances.

In this study, we further the conceptual understanding of human-robot interaction (HRI) with three key contributions. Firstly, we challenge the prevailing paradigm that robots should inherently always offer assistance, raising the essential question: "*Under what circumstances should a robot offer help?*" Secondly, we present a systematic way of considering socially appropriate assistance in HRI. Thirdly, we introduce a theoretical model that empowers researchers to design robots capable of discerning the appropriateness of offering help to human users. We illustrate the practical insights of the model with various example scenarios.

II. Background

Studies on help have primarily focused on "formal" contexts, wherein the roles and expectations of assistance are well-defined. Within these contexts, assistance often takes the form of explicit, task-oriented interactions, where the helper's role is clear, and the recipient's need for aid is typically acknowledged. These scenarios provide a structured environment where help is readily identifiable, such as healthcare providers administering medical treatment, lawyers giving legal advice, or educators teaching in classrooms. In such formal settings, the parameters for assistance are guided by established protocols or are likely to be communicated by the help recipient.

The field of HRI has substantially contributed to the understanding of formal assistance dynamics, as robots are traditionally designed for well-defined roles and established expectations [13], [14]. Researchers have extensively examined scenarios where assistance is clearly delineated and often initiated by explicit user requests or specific task-oriented interactions [15]. For instance, numerous studies have explored the collaboration between robots and healthcare providers [16], where robots assist in medical procedures under the guidance of professionals [17], [18] or ensure adherence to medical protocols [19], [20]. Similarly, studies have explored the interaction between robots and educators in classroom settings [8], where robots supplement teaching activities by offering structured explanations, instructional materials, and encouragement [21], [22].

However, as robots transition from controlled environments to the multifaceted landscape of naturally occurring, everyday human interactions, the concept of help extends beyond formal boundaries. In unscripted, informal situations, the decision to help becomes more intricate [23]. For instance, consider the scenario of a robot assisting a user in preparing a meal. While the task's goal is evident, the boundaries between helpful intervention and overinvolvement are less clear. The decision to offer help is compounded by subjective factors, such as the user's proficiency, preferences, and comfort with receiving aid. As such, a need arises to uncover facets of assistance that go beyond mere task utility.

A. Benefits of Socially-Aware Assistance

The voluntary nature of informal help reflects a nuanced understanding of social dynamics, user needs, and the subtleties that dictate when assistance is welcomed or better left unoffered [4]. Consider a scenario where a robot is assisting an elderly person with household chores. In this context, socially appropriate help involves the robot offering support for tasks such as light cleaning, fetching items, or even providing reminders for medication schedules. The robot's physical presence and proactive assistance create a seamless blend of convenience and companionship, enhancing the user's daily routine. However, if the robot continuously interrupts the user's work with unsolicited advice or attempts to take over each task, it would be socially inappropriate help [24], [25]. Such overbearing actions could lead to feelings of disempowerment and frustration, undermining the user's sense of autonomy and self-sufficiency. Likewise, if the robot were to fail to offer help when needed, it would also be deemed socially inappropriate behavior.

The distinction between socially appropriate and inappropriate help is evident in this scenario. Socially appropriate help enhances the user's work by providing timely and valuable support while respecting the user's autonomy and involvement. In contrast, socially inappropriate help involves excessive interference and disregards the user's agency, potentially undermining the quality of the task and the user's sense of autonomy [26]. In summary, help should be timely, useful, and aligned with the user's needs and preferences.

B. Expectations of Robots as Helpers

Psychological literature has explored the factors that govern the decision to offer help in human interactions in informal contexts [27], [28]. Researchers emphasize that individuals intuitively weigh the potential gains (e.g., social rewards, reciprocity, and emotional satisfaction) against the potential losses (e.g., investment of time, effort, and resources) when deciding whether to help others. This cost-benefit analysis is a core aspect of human decision-making across various everyday contexts. For instance, when deciding to help a friend move, an individual may consider the time commitment, physical effort, and potential inconvenience (cost) against the sense of accomplishment, strengthening of the friendship, and potential reciprocity in the future (benefit). Importantly, for humans, helping is a discretionary act.

In contrast to humans, it is generally assumed that robots should be readily available when needed and always willing to help users [29], [30], [31]. In other words, we naturally expect robots to be assistive and considerate. This implies that the robot's own gains and losses should not be primary factors in its decision to help. Instead, the robot should consider the utility and cost for the person receiving assistance.

C. Help Utility and Cost for the Help Recipient

Similar to the cost-benefit analysis for the helper discussed above, studies on human interaction describe factors that go into the utility and cost from the perspective of the person receiving help [32]. For one, accepting help will naturally carry a certain benefit for the recipient in terms of making the task easier or simpler. We can call such benefit *task-related utility*, which largely depends on the specifics of the task and situation. Apart from task-related utility, there can also be a *social utility* arising from the feelings of companionship and security that a person gets when offered help. These benefits depend on the relationship with the person providing help and are generally greater in relationships characterized by trust and rapport. In less positive relationships, the benefits are less and may even become a cost, such as in the case when a person strongly dislikes interacting with robots.

Despite the benefits of receiving help, people often fail to ask for help or do not appreciate it when offered to them. Several explanations have been put forth to account for this behavior [33], [34], [32], [35], [36], generally framed as costs of receiving help. They can be broadly grouped into four types: external image cost, self-image cost, relationship-to-helper cost, and skill improvement cost.

Being seen receiving assistance can lead to negative social judgments from others, either the helper or bystanders [36]. Receiving help can give the impression that the recipient is incompetent, lacks the ability, or is dependent on others [34], [4]. This apprehension of being negatively evaluated by others can lead individuals to refrain from seeking or accepting help even when they might genuinely require it.

While this concern is often present for human helpers, it is likely less pronounced when a robot offers help [37].

Apart from influencing our image in other people's eyes, accepting assistance may also potentially undermine one's own self-image, resulting in reduced feelings of achievement, autonomy, or self-esteem [38], [39]. Accepting help implies that recipients are not completely responsible for the product of their activity. To protect their ownership of a task, people may prefer to struggle with the task rather than seek or accept assistance [33]. Such effects are closely tied to the recipient's personality [40]; for instance, people with a strong self-reliance may be more averse to getting help.

Moreover, the recipient may worry about the potential downside that providing help has for the helper and how it will affect their relationship. Recipients may consider the effort that the helper will need to invest [33] or the later obligation to repay the favor [32]. Though this is generally true for human helpers, it is possible that when the helper is a robot, the recipient will have fewer such considerations and this type of cost will be lower.

Finally, in the context of learning, training, or rehabilitation tasks, the act of performing the task itself holds intrinsic value for the individual. In such cases, the robot should exercise caution in offering assistance, as excessive help may deprive the individual of the chance to challenge themselves, learn from their mistakes, and build competence over time.

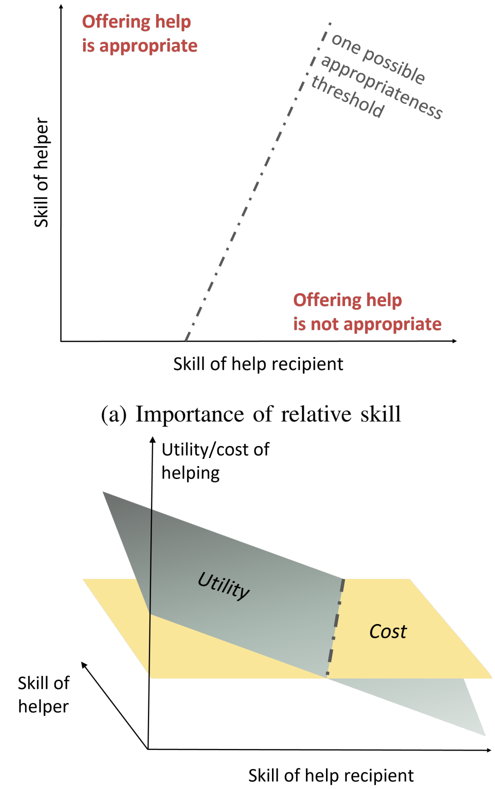
III. Theoretical Model of Offering Help

A. Appropriateness Depends on Skills

Our first observation is that the appropriateness of offering help is linked to the task-related *skill* (expertise) of both the helper and help recipient [41], [42]. We postpone discussing how to define skill until later, but in general, we can consider skill as one's level of ability to do a task. The skill of an individual or a robot will generally differ from task to task.

To understand what we should expect from a model of the appropriateness of help, let us begin with an informal deliberation on how the appropriateness of offering help changes based on skill. A graph of the help recipient's versus the helper's skill is sketched in Fig. 2a. When the skill of the helper is higher than the skill of the help recipient (upper left corner in the graph), the help will typically be welcome. In most situations, it will be rare for someone who can barely do a task or can only do it badly or ineffectively to reject an offer to have it done by someone else. On the other hand, if the help recipient is very skilled and a help offer comes from someone whose skill is quite low (lower right corner), such help would be of little, if any, value. The help recipient would likely find such an unnecessary offer to help inappropriate or even offensive unless there is some social benefit, as discussed later.

Situations between the above two are less clear-cut. When both agents have relatively low skills (the lower left corner of the graph in Fig. 2a), whether the offer to help will be welcome depends on the specifics of the task and situation. For example, even when we have low skills, if the task is simple and short and we are not in a hurry, we might not want anyone's help. Yet, if the task is long and/or urgent, we may welcome any help we can get, even from a low-skilled helper. In the case when both have high skills (upper right corner), the appropriateness will also depend on the situation; however, it will generally be less likely that the help will be perceived as needed. The recipient will mostly be comfortable doing the task themselves, and only if the task is significantly long, difficult, or urgent they might prefer to get additional help. The example threshold sketched in Fig. 2a denotes the boundary of appropriateness in offering help.



(a) Importance of relative skill

(b) Threshold is defined by utility and cost

Fig. 2: Modeling appropriateness to offer help.

B. Determining the Appropriateness

Where does the appropriateness threshold lie? To define this, we follow the insights from the psychological literature on helping described in Section II-C, which suggests that what determines if offering help is appropriate will depend on the relation between the utility and cost of getting help. Namely, if the utility is higher than the cost, it will be considered appropriate as illustrated in Fig. 2b.

As discussed in the previous section, the appropriateness depends on the skills of the helper and the recipient. What is actually changing with skills is the utility of the help for the recipient or, more precisely, the task-related utility. The utility of help is thus gradually increasing from the lower right corner to the upper left corner of the skill-skill plane and defining a curved 2D plane.

The cost of receiving help can largely be thought of as independent of skills. The cost defines a plane parallel to the skill-skill plane. The line where the utility and cost planes cross is where the offer for help switches between inappropriate or appropriate; in other words, this intersection defines the threshold in Fig. 2a.

C. Examples of Modeling Skills and Utility

The above model is still general as it does not define exactly what skills, utility, or cost stand for. This will depend on, for example, the type of task, the specific helping action to be executed, or what is the most important outcome. We will consider several examples to illustrate how one can deliberate about offering help and what the thresholds may look like in specific cases.

1) Parallelizable task, utility as saved time: The utility of helping will depend on how the help is executed. We first consider *parallelizable* tasks in which the robot can help by working together with the person on the tasks.

It may be intuitive to assess one's skill based on the execution time. For example, a person's skill level can be inversely proportional to the time it takes the person to complete a task. With this definition, a person taking twice as long to complete a task will have half the skill level. For now, we assume that the skills in a parallelizable task are additive, though this may not always be the case.

Using such a definition of skill, one way to define the utility of receiving help is by the total time the person saves by being helped. Accordingly, the utility of help will be equal to the difference between the time the person alone does the task and the time they would spend doing the task if the robot were to help.

Instead of just time, we may also consider the total saved effort of the person. Help may influence the effort in different ways. For example, it could simply affect the time it takes to complete a task, while the person's effort per time remains the same. Here, the total saved effort will simply be proportional to the saved time. Alternatively, help could change the effort per time but not affect the task time, which would have a similar effect[1]. Though other definitions are possible, we use "utility proportional to saved time".

Following the above definitions, the time it would take a human with skill s_h to do a task is proportional to $1/s_h$, and the time it would take both the human and robot when working in parallel (with additive skills) is proportional to $1/(s_h+s_r)$. The utility U of help as the time saved will thus be defined by the difference between these terms:

$$U(s_h, s_r) \sim 1/s_h - 1/(s_h + s_r) \tag{1}$$

Fig. 3a shows the graph of the utility values in such case. The appropriate-inappropriate threshold will follow the contours of the utility, with the exact place of the threshold depending on the cost of getting help. The dash-dotted line shows one such example threshold. Although hard to notice in the graph, if a robot is not able to do the task (skill is zero), the task-related utility is always zero (but remember that this is just the task-related utility; the total utility of help may be different since it also includes the social utility, as discussed in Section II-C). In contrast, the utility becomes very high when the person's skill approaches zero.

2) Non-parallelizable task, utility as saved time: We next consider a task that does not allow working together and requires either the robot or person to do it. Here, helping consists of the robot doing this *non-parallelizable* task instead of the person, and the person will not have to spend time or effort on the task. Therefore, the total time or effort that is saved for the person equals the time or effort that they would spend on the task if there was no help:

$$U(s_h, s_r) \sim 1/s_h \tag{2}$$

The graph of help utility for such a case is shown in Fig. 3b, with the line showing one possible resulting threshold.

3) Non-parallelizable task, utility as success rate: For some tasks that are executed repeatedly, it may be appropriate to define the skills and utility in terms of the ability to finish the task. The percentage of successfully finalized tasks could thus define skill, and an appropriate definition for the task-related utility may be the increase in success rate when help is received. The formula for utility then becomes:

$$U(s_h, s_r) \sim s_r - s_h \tag{3}$$

This utility can become negative if $s_r < s_h$ as, in this case, the success rate would decrease, i.e., the robot's help would lead to even worse results. Fig. 3c shows the resulting utility contours.

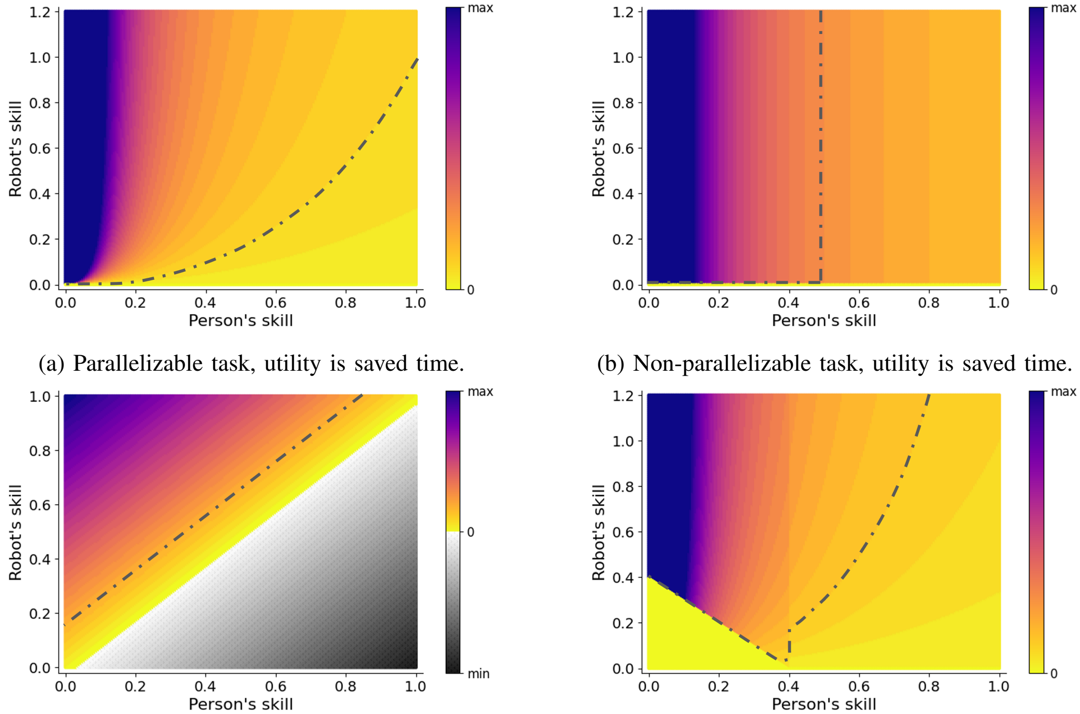
4) Effect of deadline or minimum required skill: The utility of help may be affected by other factors, such as the task's urgency. For example, if we assume there is a deadline by which the task needs to be finished, no combination of the person's and robot's skills will be able to meet the deadline.

For illustration, let us consider the case of a parallelizable task with utility as saved effort analyzed in Section III-C.1. If there is a deadline and both the person and the robot have very low skills, even doing the task together may not be enough to meet the deadline (i.e., $1/(s_h + s_r)$ is lower than a threshold T defined by the time to the deadline). In such cases, the task-related utility of helping can be assumed to be zero. In addition, we could assume that if someone who cannot meet the deadline by themselves (i.e., $1/s_h < T$) gets help and, as a result, can finish the task in time, they are going to find help even more valuable. This would manifest as an extra increase of utility whenever the person's skill is below the minimum necessary level.

The expression for the utility could then be written as:

$$U(s_h, s_r) \sim \begin{cases} 0 & \text{if } 1/(s_h + s_r) \leq T, \\ U_1 + c & \text{if } 1/(s_h) \leq T \text{ and } 1/(s_h + s_r) > T, \\ U_1 & \text{otherwise} \end{cases} \tag{4}$$

[1]For example, assume one is transporting books by carrying 20 books at a time. The robot could help by carrying another 20 books together, halving the total time to do the task, or it could carry 10 of the 20 books, thus halving the effort per time but with the task time remaining the same. Assuming the effort per time is proportional to the number of carried books, the total saved effort will be the same in both cases.



(a) Parallelizable task, utility is saved time.

(b) Non-parallelizable task, utility is saved time.

(c) Non-parallelizable task, utility is success rate improvement.

(d) Parallelizable task, utility is saved time, fixed deadline.

Fig. 3: Contours of task-related help utility for different tasks and skill/utility definitions.

with U_1 being the utility from equation (1) and c a constant.

The resulting effect on the help utility is plotted in Fig. 3d. This qualitative difference was also identified in [32], where the authors named such cases "necessary help" and distinguished them from the class of "convenient help" for which the person is capable of completing the task even without help.

If instead of a deadline, there was a minimum skill level that needs to exist to even be able to do the task, in the considered example, this would have the same effect as a fixed deadline as depicted in Fig. 3d.

D. Deciding Whether to Offer Help or Not

Once we know where the threshold lies and what the skills of the person and robot are, making the decision to offer help is straightforward: we judge which side of the threshold we are on (Fig. 2). So, a simple algorithm to decide when to help would then be to establish the threshold based on the balance between utility and cost, estimate the skill levels, and find where they are with respect to the threshold.

In practice, several issues like uncertainty may also need to be considered. However, we leave this for future work.

IV. Illustrative Examples

To demonstrate the practical application of our theoretical model, we present a series of example interactions inspired by recent research that exemplify the interplay of factors within the proposed model. These illustrative vignettes reveal how the robot's assessments of skills and the various factors contributing to the cost and utility of help converge to shape the robot's choice to offer help.

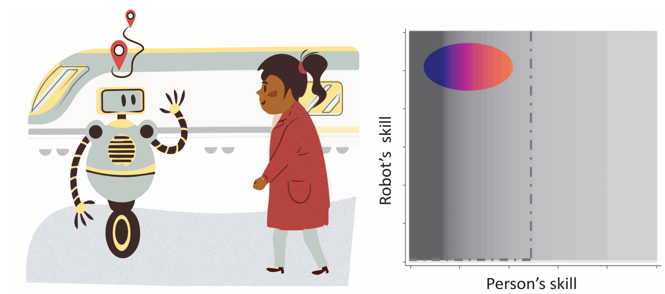


Fig. 4: A robot decides whether to offer help to a traveler who appears lost and rushed to catch their train, considering the situation's urgency and the potential value of assistance.

A. Navigating Public Transportation

Robots have been increasingly deployed to interact with individual users in public spaces [43], [44], [45]. Our model presents several considerations for researchers developing robots that seamlessly integrate into public spaces. For instance, imagine a robot designed to assist travelers in a busy subway station (Fig. 4). A passenger, Sarah, is looking at a subway map, seeming a bit lost. The robot's sensors detect her perplexed expression. The robot must now decide whether it is socially appropriate to offer help to Sarah.

Using the proposed model, the robot assesses its own navigation skills, Sarah's body language indicating uncertainty, and the urgency of helping her before she misses her train. It also considers the potential social cost of offering assistance—some individuals might feel uncomfortable receiving help from a robot in public. However, the robot also recognizes the value of providing guidance.

Informed by this analysis, the robot approaches Sarah, asking if she needs help finding her destination. Sarah smiles in relief, accepting the robot's offer. The robot provides clear directions and ensures she boards the correct train.

By accurately assessing skills, urgency, cost, and utility, the robot successfully engages in a socially appropriate interaction. It intervenes when its assistance is valued, thus fostering positive rapport between humans and robots and demonstrating the practical significance of the proposed model in a real-world situation.

B. Cooking Collaboration

Robots have seen increasing adoption in home settings, where they interact closely and frequently with individual users [46], [47], [48], [49]. Our model provides a valuable framework for researchers striving to develop home-assistance robots. For example, consider a robot assisting a person in preparing a complex recipe (Fig. 5). The robot assesses its skill and the person's culinary expertise. It assesses the urgency of the task (e.g., a dinner party), potential task completion cost (burning a dish), and benefits of successful collaboration. The robot's decision hinges on providing just the right amount of guidance and intervention, ensuring a delicious outcome while preserving the person's sense of accomplishment.

Robot with Advanced Culinary Skills: Envision a robot assisting a home cook, Alex, in preparing a complex dinner. The robot has been integrated with advanced culinary knowledge and can execute intricate cooking techniques flawlessly.

As Alex begins the meal preparation, the robot monitors the kitchen environment. It assesses its own culinary skills and compares them to Alex's cooking expertise, considering factors such as ingredient familiarity, technique mastery, and familiarity with the recipe. The robot also evaluates the urgency of the situation—if the dinner is for an important event, its timely execution is crucial.

The robot takes into account the potential cost of intervention—stepping in too frequently could diminish Alex's sense of accomplishment, undermine the personal touch of the meal, or even hinder her skill development by preventing him from fully engaging with and mastering certain cooking techniques. On the other hand, offering help at the right moments could enhance the overall cooking experience and ensure a successful outcome.

Here, the robot's role is not merely utilitarian; it's a collaborative partner. As Alex prepares the meal, the robot discreetly offers suggestions for enhancing flavors, adjusting cooking temperatures, and optimizing plating techniques. Its assistance is not intrusive; instead, it complements Alex's skills and enhances the final dish.

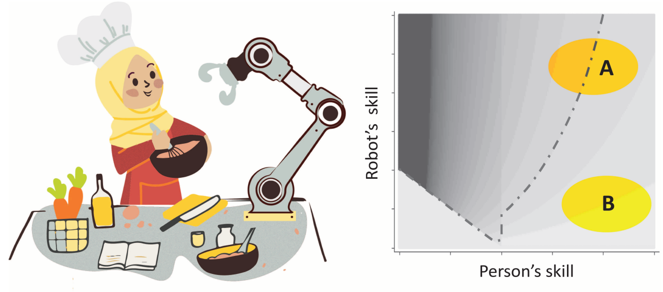


Fig. 5: Relative expertise plays a crucial role in determining the social appropriateness of a robot's offer of help. The user's high skill in cooking presents two scenarios, where (A) the robot has advanced culinary skills, and (B) the robot has limited culinary skills.

The robot's decision-making process is guided by its analysis of skills, urgency, cost, and utility (Fig. 5-A). It intervenes when its help aligns with the complexity of the task, Alex's preferences, and the importance of the dinner's outcome. By offering subtle guidance and support, the robot enhances the overall cooking experience and contributes to the successful creation of a meal that reflects both Alex's culinary skills and the robot's expertise.

Robot with Limited Culinary Skills: Now, consider the same cooking collaboration scenario, but this time, the robot assisting Alex has limited culinary skills and is not as adept at executing complex cooking techniques. Here, the robot places more emphasis on understanding the level of Alex's cooking expertise and the situational factors of the dinner. It assesses whether offering assistance would genuinely contribute to the cooking process or potentially hinder Alex's creative input. The robot acknowledges the potential cost of intervening too often with limited knowledge, which could lead to a lack of trust and frustration on Alex's part.

The robot's decision becomes more selective (Fig. 5-B). Instead of actively providing cooking suggestions, it might choose to offer assistance in other ways, such as prepping ingredients, setting timers, or managing cooking utensils. In this adapted example, the robot's limited culinary skills lead it to exercise discretion in its assistance. Its decision to offer help is influenced by the recognition of its own limitations and the desire to contribute in ways that genuinely enhance the cooking process due to the importance of the outcome to its human user.

C. Long-Term Companionship

The domain of eldercare assistance [50], [51] and long-term companionship [52], [53] with robots has garnered significant interest. Our model offers guidance for researchers in this expanding field, providing a systematic framework for designing robots that demonstrate long-term, appropriate assistance. Consider a scenario in an eldercare facility where a social robot has interacted with its user, Bob, for several months (Fig. 6). The robot has become integral to Bob's daily life, seamlessly helping with household tasks, providing companionship, and offering emotional support.

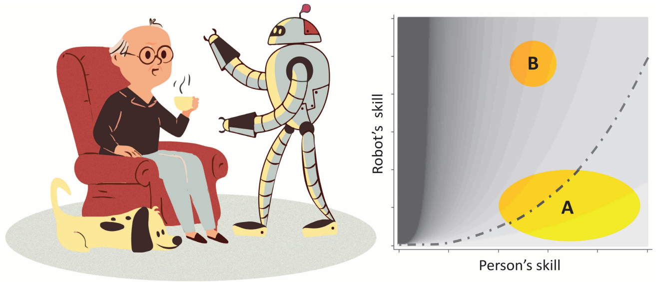


Fig. 6: The decision to help evolves over time. Initially, the robot has high uncertainty about the user's needs and preferences (A). As the relationship deepens, the robot gains an accurate and nuanced understanding, leading to more confident and appropriate offers of assistance (B).

In earlier interactions, the robot was cautious about offering help to Bob. It would often wait for explicit requests before intervening, as it still learned about Bob's preferences and tendencies (Fig. 6-A). In the short term, the robot curated questions to probe Bob's skill level at various tasks and his receptiveness to an offer of help. However, their relationship deepened over time, and the robot gained a nuanced understanding of Bob's needs and preferences.

One day, Bob expresses an interest in engaging in a painting activity in the facility's communal art space. As he prepares to start, the robot observes his actions and anticipates that he may need assistance. Considering their history and recognizing Bob's preferences, the robot offers him help without waiting for a request (Fig. 6-B). It suggests ways to set up the painting area and provides tips for achieving even brush strokes.

Importantly, their established rapport influences the robot's decision to offer help. As the human-robot relationship positively evolves, Bob subconsciously attributes less cost to the robot's offer of assistance. He understands that the robot's intentions are genuine and that its help is designed to enhance his tasks rather than intrude upon his autonomy.

V. Conclusion

With the growing integration of robots into our everyday activities, discerning the social appropriateness of offering assistance is essential. Our study challenges a conventional assumption that robots should always offer assistance, presents a systematic way of deliberating socially appropriate assistance in HRI, and introduces a theoretical framework that guides researchers in designing robots that can offer socially appropriate assistance.

While this study has touched upon the concepts of familiarity, rapport, and trust, measuring these dimensions in an accurate yet natural manner during real-world interactions remains an ongoing challenge. As we explored how these factors influence a robot's decision-making process, future research should explore methods of quantifying these constructs to demonstrate their measurable impact on socially appropriate assistance.

We also recognize that ethical considerations emerge as significant factors. As robots gain deeper insights into users' lives and preferences, questions about data security, user safety, and personal privacy become paramount. Striking the delicate balance between personalized assistance and respecting user boundaries poses ethical challenges that warrant careful consideration.

Drawing from an array of psychological findings traditionally focused on human-human interactions, we presented a robust and systematic way of thinking about socially appropriate assistance in human-robot interactions. The resulting framework provides both theoretical insights and practical guidance for robots navigating complex social scenarios, enabling them to extend a helping hand when socially acceptable and beneficial.

Acknowledgments

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