Designing Social Interactions for Learning Personalized Knowledge in Service Robots

Shengchen Zhang[1] and Xiaohua Sun[1]*

College of Design and Innovation, Tongji University, Shanghai, China
{shengchenzhang,xsun}@tongji.edu.cn

Abstract. Service robots are required to effectively gather and utilize personalized knowledge in a working environment, especially through social interaction with their users. Existing works have shown the significant influence of interaction design on the efficiency, accuracy, and user experience of learning interactions. Designing social interaction for learning personalized knowledge poses new challenges for HRI designers, which signifies a need for designerly knowledge in the form of tools, methods, and effective patterns. In this paper, we present a toolkit to help the design of social interaction with service robots for the learning of personalized knowledge, by informing designers of key challenges and potentially applicable patterns to help ideation. We discuss five key challenges for interactively learning personalized knowledge based on existing literature, and propose ten interaction design patterns that can be employed to help the ideation. We then present a preliminary evaluation of the toolkit through workshop sessions with HRI designers. Questionnaires and semi-structured interviews were used to gather feedback from the participants. The results show the ability of the toolkit for aiding ideation and its potential for flexible ways of use, and point towards future directions to improve and expand the toolkit.

Keywords: Social human-robot interaction · Design heuristics · Design toolkit · Robot knowledge.

1 Introduction

As services robots are increasingly deployed into the real world, they are envisioned to complete complex tasks based on high-level goals and interact with users in an easily-understandable way[11]. Moreover, emphasis is put on the ability to adapt to user traits and preferences in order to provide better collaboration, personalized service, and robust interactions[21]. This requires robots to effectively gather and utilize personalized knowledge about the user and related objects, places, and events in the robot's working environment[9][23]. Such knowledge is specific to the robot's environment and cannot be observed before deployment. Therefore, many researchers have proposed methods for robots to learn the knowledge through the detection of human activity, social cues, and

* Corresponding author.

many more[21], and by interacting with humans to acquire the knowledge that is needed[6]. To this end, many methods of knowledge acquisition using social interaction have been proposed as well, such as learning the preferred way of executing a task through dialogue[17], or interactively clarifying an unknown reference to an item[18]. Current research has also explored the effect of different manners of interaction on robot learning. It has been shown that the design of a robot's questions can significantly impact the quality of data gathered[20], and different interaction modes can affect user perception of the robot as well as learning accuracy[2].

However, less emphasis is put on the "designerly" aspects, especially tools and methods to aid the design of personalized knowledge learning interactions under concrete service scenarios. It will be especially challenging for professional interaction designers and engineers that create and implement robot services for specific working environments and tasks. They are tasked with designing interactions that are grounded in the service context, can handle complex situations in real service scenarios, and often for repeated or long-term interaction. This requires the design to account for practical issues such as user attitude towards a learning robot and the effects that the learning interaction may have on user response and data quality. While existing works each provided general guidance, HRI designers can greatly benefit from a curated set of patterns and tools to help the identification of potential challenges and the ideation of suitable interaction design.

In this paper, we present a toolkit to help the design of social interaction with a service robots for the learning of personalized knowledge. We identify five key challenges for interactively learning personalized knowledge based on existing literature, and discuss the constraints and opportunities they impose on the design of the learning interaction. We then propose ten interaction design patterns that can be employed to help the ideation of social interaction for service robots to learn the personalized knowledge of users. The challenges and patterns are presented as a design toolkit in the form of cards. The toolkit is evaluated by organizing workshop sessions, in which HRI researchers and participants with HRI design experience used our tools to improve an existing interaction flow of a service robot. We conducted semi-structured interviews after each workshop session with a focus to evaluate the tool's *ease of understanding*, *informativeness*, *usefulness*, and *ease of incorporating into existing designs*, as well as to collect suggestions of improvement from our participants.

Our contributions are as follows:

- We identified five challenges for HRI designers when designing social interactions for learning personalized knowledge under a concrete service context.
- We proposed ten interaction design patterns to address these challenges that support the ideation and design of social HRI.
- We developed a design toolkit based on the challenges and patterns, and presented an evaluation of the toolkit through workshop sessions with HRI designers.

2 Related Works

2.1 Tools and patterns for HRI design

Löwgren[16] identified heuristics, design tools and methods, and patterns as some of the important types of intermediate-level knowledge in the field of human-computer interaction. Lupetti et al. [15] argued similarly for HRI, pointing out the importance of designerly knowledge in HRI, and calling for investigations into the conceptual implication of HRI research artifacts.

Much research into HRI design has taken the form of collections of concepts, ideas, or patterns. Alves-Oliveira et al.[1] developed a collection of metaphors for the roles of a robot to provide aid in examining new human-robot relationships. Kang et al. developed a toolkit in the form of cards to help design social human-robot interaction. Kahn et al. [10] introduced the concept of design patterns, and proposed eight HRI patterns that can be employed to enhance robot sociality. Sauppé and Mutlu[22] derived interaction patterns from human-human dyadic interaction and developed a prototyping tool to aid the application of these patterns in HRI design. Our previous work[23] on designing robot interfaces to communicate its knowledge has also taken the form of a collection of patterns.

In line with previous works, this paper adds to the designerly HRI literature by presenting a toolkit containing interaction patterns for learning personalized knowledge.

2.2 Robot learning through social interaction

Learning through social interaction has been proposed as a way to utilize the knowledge of humans to improve robot capabilities. Many works examined the design and effects of socially-guided learning in service robots. Lockerd and Breazeal[13] proposed the concept of socially-guided machine learning — learning tasks and skills from end-users through social interaction. Many works proposed effective methods for learning through social interaction. Chao et al.[4] developed a system that involves human teachers through active learning. Gervasio et al.[8] proposed a method to automatically learns question-asking strategies.

Researchers have also studied the effect of different interaction modes on learning efficiency. Rosenthal et al.[20] studied how the design of a robot's questions influences the quality of data gathered. Cakmak et al. [2] showed how different interaction modes can affect user perception of the robot as well as learning accuracy. Cakmak and Thomaz[3] also showed the varying efficiency of different question-asking modes.

Existing research has shown that learning through social interaction could be an effective method to account for complex tasks in service scenarios, and pointed out that the manner of interaction has a significant impact on learning accuracy, efficiency, and user perception. Our toolkit is prompted by these insights to help HRI designers take into account these factors.

2.3 Personalized Knowledge in service robots

It has been recognized that personalized knowledge can help enable adaptive robotic services. Olivares-Alarcos et al. provided an overview of using ontology to represent and utilize knowledge in robots[19]. Our previous work[23] further identified the types of knowledge related to specific service situations for service robots, including objects, environment, users, actions, and context.

Many methods have been proposed to learn personalized knowledge interactively. Rossi et al.[21] provided a survey of methods for user profiling, which includes interactive methods to learn user-related knowledge. Previous research has also developed designing interfaces to help domain experts directly view and manipulate the knowledge graph in a robot in order to understand and operate it[12]. Researchers looked into developing a set of human-friendly vocabulary to build robot ontology[5], which has the potential to help communicate robot behaviors in interactive knowledge learning.

Our work is informed by the challenges and types of knowledge learning tasks identified by current research. Existing cases also provide material for analysis that helps produce the patterns in our toolkit.

3 Design Toolkit

The proposed toolkit consists of two set of cards: *challenges* and *patterns*, as shown in Figure 1 and 2. The content of the cards are detailed in the sections that follow, along with a discussion of the curated literature and cases that informed its inclusion.

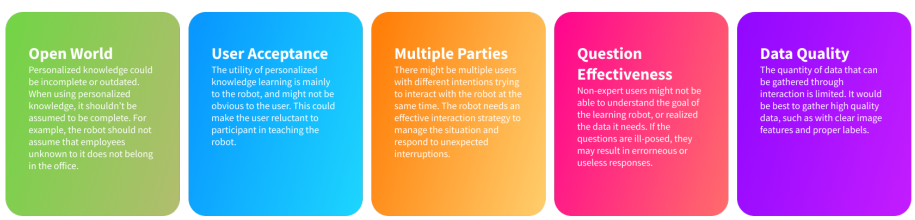

Fig. 1. The *challenges* cards. Each card consists of a title naming the challenge, and a short description providing the reasoning and issues.

The *challenges* set consists of five cards that describe the issues that needs to be taken into consideration when designing HRI that utilize or are aimed at learning personalized knowledge. These challenges stem from the intrinsic properties of personalized knowledge (*Open World*), the users of the service robot (*User Acceptance* and *Multiple Parties*), as well as the design task itself (*Question Effectiveness* and *Data Quality*).

Fig. 2. The *patterns* cards. Each card consists of a title and a short prompt in the form of a question, followed by a example of applying the patterns under a concrete service scenario. The cards are color-coded to depict their connection to the challenges.

The *patterns* set consists of ten cards containing potentially applicable patterns that serves as prompts for ideation. Each of the cards corresponds to a certain challenge in the *chalenges* set, indicating the challenge it could be user to address.

3.1 Open world

The first challenge stems from the property of personalized knowledge. In contrast with commonsense knowledge, personalized knowledge could often be incomplete or outdated. When making use of personalized knowledge, it should not be assumed to be complete and error-free. For example, the robot should not assume that employees unknown to it do not belong in the office, and objects whose location is unknown could still be present in the current space. This poses a unique challenge for HRI designers to bear in mind when designing interactions that utilize or aim to learn personalized knowledge. The lack of knowledge could be the result of various possibilities, which should be addressed differently to achieve a natural and fluent user experience. Two design patterns are proposed to address this challenge: *just ask* and *socially-assisted robotics*.

Just ask This pattern is directly prompted by works related to active learning through social interaction, where robots ask verbal questions to learn perception and task skills[2][3]. The designer is prompted to add an interaction step to directly query the user when there could be a lack of personalized knowledge. An example of this solution could be that when encountering an unidentifiable user, rather than assuming it is a first-time encounter, the robot could apologize for not recognizing the user, and then ask for their identity.

Socially-assisted robotics The name is a twist on the name of the field socially-assistive robotics, which develops social robots to assist humans. The core idea of this pattern, in contrast, is to enable users to help the robot through social interaction. This pattern is inspired by relevant discussions in HRI around robots as citizens within the society. Lupetti and Giaccardi [14] proposed a concept named "the handleable robot", where they address the issue of navigating complex outdoor intersections by turning to the robot's shared membership in the community and asking for help from nearby pedestrians. The designer is prompted to take advantage of the fact that users could be considered domain experts on personalized knowledge, and design a mechanism to let other users provide the missing information or help the robot.

3.2 User acceptance

The second challenge stems from the attitude of the users. In the context of a service robot, the experience and acceptance of the user are considered vital to the quality of the service. This has led to two issues that require balancing from the designer.

The first issue concerns utility, specifically utility to the robot versus utility to the user. For a service robot, it is usually expected to provide a certain utility to the user. However, the utility of personalized knowledge learning is mainly to the robot, and may only enhance the service quality of the robot in the long run, which might not be obvious to especially non-expert users. This could make the user reluctant to participate in teaching the robot. Moreover, in long-term interaction, repetitive asking could significantly impact user experience. This challenges HRI designers to produce more engaging learning interactions, or try to make the utility of robot learning more obvious.

The second issue concerns automation versus user control. Chao et al. investigated the user's attitude towards an active learning robot and found that "balance of control between the robot and the human is a parameter to tune carefully when designing an interaction", as the completely robot-initiated active learning could deprive the user's sense of control in the learning process[4]. This challenges HRI designer to devise more flexible learning interactions that enable the user to shape the robot learning process. Two design patterns are proposed to address this challenge: *back-up plans* and *it's a feature!*

Back-up plans Fong et al. [7] showed that users may disengage the robot when it repeatedly asks the same question. In response, they suggested that contextual dialogue management could be a solution. In this card, the designer is prompted to consider whether a question is asked differently according to context. An example would be that the robot can record the times it has asked a question to a user. When a question has to be asked a second time, the robot could express awareness of the situation, such as by apologizing for repeated asking.

It's a feature! This pattern is in direct response to the issue of utility to the user. The designer is prompted to try turning a learning interaction into something that could also provide utility to the user. The example given is that at environments like offices and classrooms, new users are introduced periodically. While learning faces by interacting with new users one-by-one would be inefficient and provide little utility to the users, a robot could be designed to contain an ice-breaking function, where the robot can help lead an ice-breaking session between the newcomers. During the interaction, the robot can learn the correspondence between names and faces along with the users.

3.3 Multiple parties

Another challenge posed by users is the presence of multiple interacting parties. There might be multiple users with different intentions trying to interact with the robot at the same time. This, in turn, could lead to mismatches between training data and labels, or cause interruptions in user demonstrations. To address this problem, HRI designers will need to devise effective interaction strategies to manage the situation and recover from unexpected interruptions.

Isolation A strategy that people often use in group settings is to isolate the person of interest through cues like posture and objects. For example, in group activities and speeches, it is often that the speaker stands up, or holds objects that signify their position. The designer is prompted to let the robot guide the person of interest to do something significantly different than others. The robot could encourage such behavior, in order to separate the speaker from the rest by a distinct posture or human-object relationship.

3.4 Question Effectiveness

The task of designing social interactions for robot learning itself poses challenges to HRI designers as well. The first challenge posed is the effectiveness of asking questions. A direct and common way for robots to learn from users is by asking questions. However, Rosenthal et al. [20] found that if the questions are ill-posed, they may result in erroneous or useless responses. They also found that users might not fully understand the intention of the learning robot due to a lack of context. This highlights the importance of designing effective questions. The following patterns are mainly derived from strategies that are shown effective by Rosenthal et al.[20].

To Err is Human The naming suggests that by properly communicating potentially erroneous results to users, the robot could handle errors in recognition more gracefully ("human-ly"). The robot's recognition results are not always accurate, and providing recognition results can help users identify errors and give corrections. For example, when approaching a user, the robot could proactively show the name of the user that is detected, or show the absence of a name in a clear manner.

Describe Uncertainty The robot could use multiple modalities to describe its uncertainty when asking questions to a user. Describing the uncertainty of the results may help users to recognize potential problems, and may improve the accuracy of their feedback. For example, when referring to an object, person, or location to a user, the robot can use descriptive expressions to convey its confidence, such as "I'm sure that...", "I guess that...", or "it should be..." This could also be color-coded to represent uncertainty.

Provide Context The robot could use multiple modalities to explain the current context to the user when asking a question. The responses provided by users are not necessarily accurate, and providing more contextual information may help users to provide more accurate responses. For example, when describing an object to the user, the robot can show relevant information such as its last seen location, photos of the object, or similar objects.

3.5 Data quality

The second challenge posed by the task of designing social interactions for learning is the quality of gathered data. First of all, the quantity of data that can be gathered through interaction is limited. It would be best to gather high-quality data, such as with clear image features and proper labels. This requires guidance on the robot's part, especially for non-expert users. Second, it is necessary to take into account inaccuracies in the robot's perception. Wizard-of-Oz user studies are common in the field of HRI, which does not account for inaccuracies. To achieve more robust interaction, the design should include interaction flows to recover from such errors. Two design patterns are proposed to address this challenge: *hands-on* and *waiting for windfalls.*

Hands-on It is commonplace in commercial products that a tutorial is presented to the user to guide data collection. An example would be Apple's Face ID, where an interactive animation is used to help users provide a higher quality facial model. The designer is invited to consider whether the robot can guide the user into doing something that better helps the robot learn, and design interactions to guide the user into performing the appropriate actions. For example, the robot could correct the way the user is holding an object, or guide the user into a specific posture.

Waiting for Windfalls In larger working environments, interaction with users might be scarce due to a low chance of encounter, further making collecting high-quality training data a challenge. The designer is prompted to let the robot utilize its idle time to go and wait for encounters at the most possible location. For example, for an office robot, it could ask for the charging station to be located at the break room, where many people would go and is suitable for social chit-chat.

4 Evaluation of the design toolkit

The proposed design tool is evaluated by organizing workshop sessions, in which HRI researchers and participants with HRI design experience used our tools to improve an existing interaction flow of a service robot. We conducted semi-structured interviews after each workshop session with a focus to evaluate the tool's *ease of understanding*, *informativeness*, and *ease of incorporating into existing designs*, as well as to collect suggestions of improvement from our participants.

4.1 Participants

Four HRI designers (F=1, M=3) unrelated to this research were recruited for the workshop sessions. The participants filled in a questionnaire on their knowledge background and past experience, where they were asked to rate their familiarity with the topics of robotics and relevant technology, HRI theory and technology, and HRI design. The scale ranged from " no knowledge", "acquainted with the topic", "familiar with the topic", and "professional/expert knowledge". Participants are also asked whether they had experience on designing HRI in general, and in particular designing HRI for a specific service scenario.

All participants reported varying knowledge in the three topics. In terms of robotics and relevant technology, two participants reported to be "acquainted with the topic", one reported as "familiar", and one of them "professional/expert level knowledge". In terms of HRI theory and technology, two of the participants reported "acquainted with the topic", one "familiar", and one "professional/expert". In terms of HRI design, two of the participants rated their knowledge as "acquainted with the topic", and two rated "familiar". One participant reported no experience in designing HRI. For the other three participants who had experience, two had designed HRI for a specific service context, among whom one had professional experience.

4.2 Procedure

The workshop sessions were conducted online using FigJam[1], an collaborative whiteboard application. Participants took part in the workshop individually. The

[1] https://www.figma.com/figjam/

workshop begins with an introduction to the general theme and procedures. Participants were then shown two videos of different robot receptionists performing greeting and guidance service in an office environment[2], in order to establish context.

Participants went through two introductory steps, introducing the types of learning tasks, and the challenges of personalized knowledge learning. At each step the facilitator introduces the concepts with a visual aid, followed by guiding the participants through a warm-up exercise, where they brainstorm examples of the concepts just discussed, to familiarize the participants with their usage. For the design toolkit, the facilitator gave an overview of the cards, and introduced one of the cards in detail as an example. The participants are then given time to read all of the cards, and facilitator answered their questions as needed.

After the introduction, the participants are given a task two improve an existing greet and guidance HRI, extracted from the two demo videos the participants saw at the beginning. They are provided with a interaction flowchart depicting the design, and instructed to complete the tasks in two steps. In the first step, participants went through the HRI process, trying to identify potential challenges related to personalized knowledge learning.

Finally, participants filled in a questionnaire asking them to evaluate the informativeness, ease of understanding, usefulness, and ease of applying into existing HRI designs. The questions are listed in Figure 3. Similar questions were then discussed in an semi-structured interview that follows.

4.3 Results

The questionnaire results were plotted and shown in Figure 3. Overall, participants unanimously agree that the toolkit helped enhance their understanding of the HRI design issues related to personalized knowledge learning, and that the cards are presented in a manner that is easy to understand. Participants generally agree that the cards can be useful in improving the quality of HRI design (mean=4.75, sd=0.5), and that the patterns presented can be relatively easily incorporated into existing HRI designs (mean=1.25, sd=0.5).

The interview recordings (67 minutes in total) were transcribed and analyzed through thematic analysis by iterative coding using ATLAS.ti [3]. During the first iteration, quotations were extracted for any comments, suggestions, reasoning, and expression of judgement. The quotations were open-coded, and the codes were grouped according to themes. In the end, three major themes were identified, the details and implication of which will be discussed in the following section.

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[2] The videos are available at https://www.youtube.com/watch?v=diid3b25CbM and https://www.youtube.com/watch?v=LT4G161ImqE. An archived version is also available at the project repository https://github.com/tongji-cdi/design-learning-hri.

[3] https://atlasti.com/

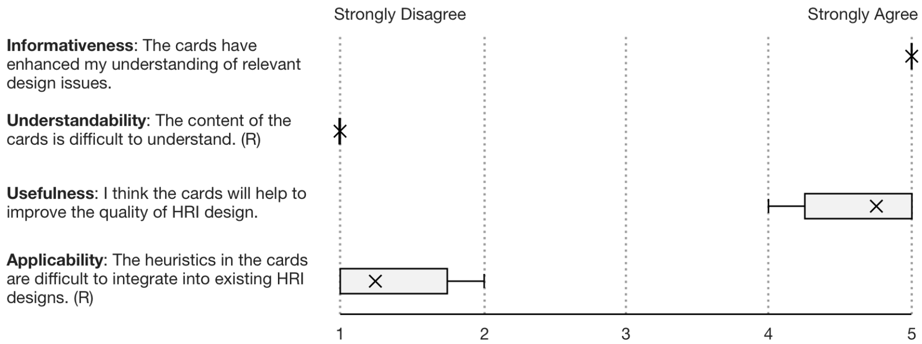

Fig. 3. Questionnaire results. Questions labeled (R) are asked in a reversed manner to improve reliability.

5 Discussion

Our interview with participants provided a more in-depth look into the effects, pitfalls, and future potential of the toolkit. We summarize and discuss notable themes that resulted from our thematic analysis below.

5.1 Aiding ideation

Participants reported how the toolkit helped their ideation process in the task. In terms of the *challenges* cards, participants noted that the challenges presented in the toolkit helped them gain understanding of the design task and discover potential problems. P3 remarked that it helped to gain a deeper understanding of the problem. P4 (who claimed expert knowledge on robotics and related technologies) commented that although he had been aware of most of the challenges individually, seeing them together in the toolkit is still very helpful. P1 described the challenges as a "checklist" that could help systematically check for potential problems in an HRI design. This suggests that the toolkit helps provide a more structured way of approaching the design task.

In terms of the *patterns* cards, participants expressed varying levels of satisfaction. Most participants described situations where the ideas in the patterns are new to them, and helped them generate solutions in the workshop. P1 noted the value of *socially-assisted robotics* in real world scenarios is not only functional, but also emotional, by referring to past experience in designing HRI for delivery robots.

> "(In the case of a door malfunction) the robot would ask a nearby pedestrian, 'can you help me close my door?' ... People are happy to help. When we conducted interviews, people would say they helped the robot. It made them feel more trusting towards the robot." (P1)

P4 thinks that the example given in *isolation* and *describe uncertainty* provided new ideas outside of technical solutions.

> "(In my past solutions) the robot used multi-modal information to try to recognize the users. But I think making this into a game to confirm identity is a very good way as well. ... I did not consider how to communicate it to users when encountering uncertainty. I think it is a good way and opens up many possibilities." (P4)

However, participants also noted cases where the toolkit was ineffective in aiding ideation. P2 mentioned that it felt restrictive that *isolation* was the only pattern in *multiple parties*, and expressed reluctance to use patterns in one category to address another challenge, even in cases he thought that they were applicable. He attributed the reluctance to a strong sense of categorization due to the visual design of the cards.

Overall, comments from the participants suggest that the toolkit was effective in aiding ideation from three aspects. First, the toolkit informs HRI designers of potential challenges and solutions, therefore enhancing their understanding of the design task. Second, by enumerating challenges in HRI design for personalized knowledge learning, the toolkit provides a structured way of discovering potential flaws in a design. Third, patterns in the toolkit highlights potential "designerly" solutions outside of technical ones, and may help broaden the search space for a most suitable solution under given service scenarios.

The comments also highlight problems with the current toolkit. First, the number of patterns may be lacking, so that it restricts the ideation of designers. Second, the visual design could be improved so that it remains informative of the connection between challenges and patterns, but also does not enforce a correspondence.

5.2 Ways of using the toolkit

During the workshop process, in addition to the general two-step process instructed by the facilitator, participants demonstrated creative ways of using the toolkit.

First of all, multiple participants used patterns across categories. P1 saw the challenges as inspirations, and used it to check for problems in the HRI design, while believing that the connection between challenges and patterns are unimportant. P4 held similar views, additionally pointing out that multiple challenges can arise in the same interaction step in the design, and highlighting the need for new patterns.

> "(Reception robot meeting new people) is a case of *open world* and *multiple parties* combined... What are the patterns to deal with two challenges at once? ... I think this is a problem of '$1 + 1 > 2$.' " (P4)

Participants also combined multiple patterns. In the case above, P4 proposed to combine *socially-assisted robotics* and *isolation*, engaging new users one by one while sending messages to office members for information and clarification at the same time.

Another interesting observation, made by P2, is that some challenges has pairs of "direct" methods and "indirect" methods as patterns. P2 then used this intuition to help generate ideas for dealing with other challenges.

> "*Open world* and *user acceptance* each had two patterns. One of them is more direct (in the way of asking), and the other is more indirect. After I realized this, when I look at other problems, I would also think whether there are direct or indirect ways of addressing this challenge."(P2)

To summarize, comments in this theme highlights the potential for elements in the toolkit to restructure and recombine. This indicates that both the challenges and patterns supports a certain degree of flexibility in the way of use, which we think is desirable for a design toolkit. Meanwhile, this also highlights a need of further structuring of the patterns, and doing so may enable designers to expand the patterns during the design process as well.

5.3 Future directions

Participants also suggested future directions as to how to improve the design toolkit. Some participants pointed out that some patterns appeared commonplace. P1 noted that *just ask* seemed to be the default solution and need not be included. P2 and P3 held similar opinions towards *multiple choices*. P3 also highlighted similarities between *hands-on* and existing solutions in fingerprint and face data collection, but thinks that it may still need to be included in the toolkit.

The need for better wording is also mentioned multiple times. P1 expressed confusion about the name "open world" and why it is a challenge, citing that intuitively all reasoning of humans are open-world. P2 considers the prompts in the *patterns* cards too abstract, yet the examples that follow are too concrete. P2 suggests adding a "intermediate-level description", such as a description of the general interaction process of a pattern. When asked which part he focused on the most during the task, P2 said he mostly focused on reading the examples given on the cards. Meanwhile, P3 commented that the prompts are helpful for verifying whether he correctly understood the pattern, and the examples were mostly used to help understanding the core idea. P3 said he spent half of the time reading the prompts.

P2 also stressed the need for real-world testing. P1 echoed this point by providing detailed accounts of unanticipated ways of interacting with a delivery robot observed in her field studies. These comments highlight a need for implementing the patterns under concrete scenarios and studying the extent of their effects.

In combination with the themes discussed above, several future directions for the design toolkit can be identified. First, the design and wording of existing cards can be improved, in terms of using more understandable wording, providing additional explanation of the patterns, and removing unnecessary emphasis on the categorization of patterns. Second, the design patterns could be refined by removing commonplace practices and include more cases from both the literature and existing artifacts. Third, future research could look into constructing a framework to systematically categorize and generate the patterns. Finally, HRI designers should be invited to contribute to the toolkit by presenting artifacts, developing patterns, as well as implementing and testing existing patterns.

6 Conclusion

This paper presented a toolkit aimed to help the design of social human-robot interactions for learning personalized knowledge. Our preliminary evaluation shows its ability for aiding ideation and the potential for flexible ways of use. However, we note that the development and evaluation of a design toolkit are never-ending, and require application in the real world. Our future work lies in the continued refinement of the toolkit through analysis of emerging artifacts, especially patterns embedded within commercial robot products and concrete HRI scenarios. Future research should also look into constructing a framework to systematically categorize and help generate these patterns. Finally, HRI designers should be invited and enabled to contribute to the toolkit by presenting artifacts, developing toolkit content, as well as implementing and testing existing ones.

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