Investigating the Levels of Autonomy for Personalization in Assistive Robotics

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ABSTRACT

Without a proper balance between robot autonomy and user control, assistive robots can be over-engineered or put too much burden on users. Determining ideal levels of autonomy is important when personalizing assistive robots to individual users. For example, contemporary robot-assisted feeding (RAF) systems encounter challenges when users sit in positions other than directly facing a table if this was its original design requirement. Solutions like manual fixation of sitting or plate positions temporarily work, but these may not sustainably ensure effectiveness and user comfort. Prior work has studied levels of autonomy desired in RAF systems but has focused on functional tasks such as food transfer. In this work, we begin investigating whether these findings hold during personalization algorithms, which may need to change outcomes and procedures based on the user and location. We tested out levels of desired autonomy in an example personalization learning algorithm with one potential user of an RAF system on the test case of adjusting to different sitting positions. Our preliminary results in this case study suggest that shared autonomy can be a good starting point for personalizing RAF systems.

CCS CONCEPTS

• **Human-centered computing** → *Accessibility design and evaluation methods*; • **Computer systems organization** → **Robotic autonomy**; • **Social and professional topics** → People with disabilities.

KEYWORDS

Adaptivity, personalization, lifelong learning, long-term human-robot interaction (HRI), robot-assisted feeding (RAF)

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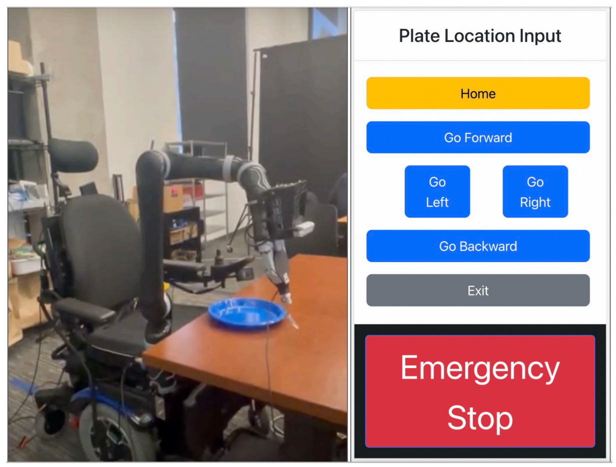

Figure 1: (a) The Assistive Dexterous Arm (ADA) is shown in a typical testing environment *(left).* (b) Smartphone app users interact with ADA using this user interface (UI) *(right).*

1 INTRODUCTION & BACKGROUND

An assistive robot designed for a specific task often has to do the same task for different users with individual preferences. A customized design may increase users' satisfaction by adjusting to their unique needs compared to a mass-produced design [10]. People with disabilities often need help with activities of daily living (ADLs), which include eating meals [2]. Modern RAF systems are useful in assisting to feed alongside caregivers or family members [6, 13]. We discuss adaptive approaches for different user positions in a robot-assisted feeding (RAF) system.

Existing RAF Systems: Several works in RAF show that full autonomy is not always the most user-preferred option [2, 3, 5]. To integrate RAF systems into complex assisted-living communities, a new framework has been proposed considering social and cultural factors beyond their technological aspects guided by a study with potential care recipients, caregivers, and domain experts [2]. Bhattacharjee et al. [2] also identified improvement needs in our RAF system, the Assistive Dexterous Arm (ADA) [6]: empowering end-users, detecting and correcting anomalies, and technical functionalities for a range of food items. Park et al. [13] developed a novel RAF system with visually-guided food acquisition. User study results revealed some improvement needs for it: user interface (UI) interaction methods, the whole system's speed, the motion of delivery, and emergency alarm for risk reduction and awareness. We aim to extend the functionalities of ADA to meet some of these improvement needs by empowering end-users with shared autonomy and providing users with their preferred UI interaction methods.

Personalization in Assistive Robotics & RAF Systems: Silva et al. [15] implemented a closed-form RAF system with a modular arm that moves its end effector to the goal (the user's mouth) based on face detection. In ADA, food transfer uses a similar face detection module, and includes personalization approaches involving both open-loop and closed-form systems as detailed in Section 2. Canal et al. [4] presented a personalization framework consisting of a Learning-by-Demonstration algorithm and a Probabilistic Movement Primitive (ProMP) formalism. A later work from Canal [5] found that integration of a user's preferences in robot-assisted tasks generates more satisfaction and pleasant experiences, and such personalization improves the robot's assistance. A framework to facilitate long-term and personalized assistance has been applied in an RAF task [11]. We incorporated some suggestions presented in [5, 11] for RAF: testing the balance of autonomy and teleoperation and determining the moment to switch between autonomy and user input. Shared autonomy has been investigated in the field of RAF, focusing on manipulation tasks [9], grasping tasks [7], and food acquisition [8], as opposed to actions compensating for changes in the user's position or environment. In an investigation of social dining with RAF systems [12], a user shared some difficulties with using ADA in different sitting positions. We investigate this problem through a user study, and present UI manipulation and vision-based techniques to facilitate personalization adding to ADA's technological adaptivity. These will inform future development of adaptive assistive robots for personalized and long-term HRI needs.

2 PERSONALIZATION APPROACHES FOR THE ASSISTIVE DEXTEROUS ARM (ADA)

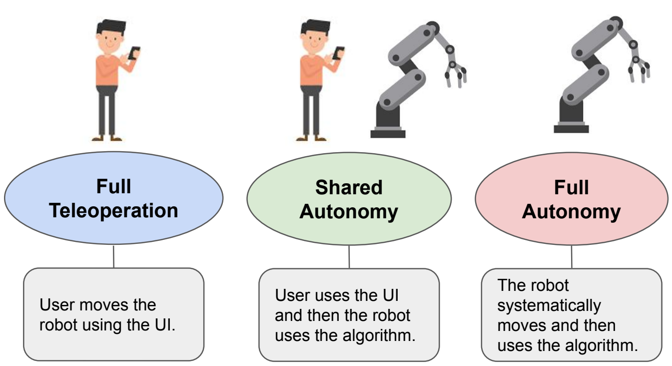

Figure 2: Personalization approaches for assistive robots.

As described by Gallenberger et al. [6], ADA consists of a wheelchair-mounted 6-degrees of freedom (DoF) JACO robotic arm. Some critiques from our lab's previous user studies [3, 12] included:

- Preference for an RAF system acting on distinct user choices
- Desire for adaptation to different user positions in RAF task

We spoke with a prominent user of ADA to study more about adapting to different sitting positions. We wanted to learn about this user's preferences to be able to fulfill critical needs. In nontraditional sitting positions, it becomes tricky to locate the full plate for acquiring food from it. Only after locating the full plate can the robot work on acquiring food from the plate and transferring it to the user's mouth. We simulated three personalization approaches (see Fig. 2) with varying autonomy levels for the user(s) to effectively use ADA from different sitting positions. One approach is **full teleoperation (FT)**, where the user tries to move the arm exactly over the plate using the UI (with no robot autonomy) to locate the full plate. FT entails an open-loop system, as there is no dependence on the position feedback of the moving arm. Another approach is a version of **shared autonomy (SA)**, where the user provides a rough guess estimate using the UI to locate the partial plate, and then the robot arm automatically does the rest to locate the full plate using an algorithm. In SA, UI-based motion is open-loop and the vision-based algorithm is closed-form. Finally, we consider a **full autonomy (FA)** approach, where there is no user input and the robot does everything autonomously. The robot first systematically scans the environment for a partial plate view, and then it uses the algorithm to locate the full plate. FA is closed form, as position information is fed back into the locating process.

3 STUDY EVALUATING PERSONALIZATION APPROACHES

We held a one-hour single-subject (n=1) exploratory study over Zoom[1]. We gathered a user's evaluative thoughts on three personalization approaches, and we learnt about the participant's eating and RAF system interaction experiences. We displayed personalization approaches through simulated videos consisting of two systems:

ADA: A wheelchair-mounted robotic arm-based RAF system (see Fig. 1(a)) that locates the full plate to acquire and deliver food items.

Web application system: An smartphone application (e.g., mainly software-mediated system)-based interaction method (see Fig. 1(b)) between robot and user. It transfers movement commands from the user to ADA, and plate detection alerts from ADA to the user.

3.1 Hypothesis

Assistive robotics is going in the direction of shared autonomy [1] and this paper adds to that literature with a focus on user-centered personalization for long-term and lifelong learning in HRI. With guidance from [3, 5] suggesting user inputs in controlling RAF systems generate more user satisfaction, we hypothesize that shared autonomy will be preferred in personalizing RAF systems.

3.2 Study Participant

This case study includes one participant who is a quadriplegic adult male. He is an assistive technology expert and has used the ADA system previously. He interacts with assistive technology by using either voice or switch (e.g., sip-and-puff) through his smartphone, although he often prefers voice control. The ADA system and smartphone app will be controlled by one or both of these methods.

[1]Zoom: https://zoom.us/

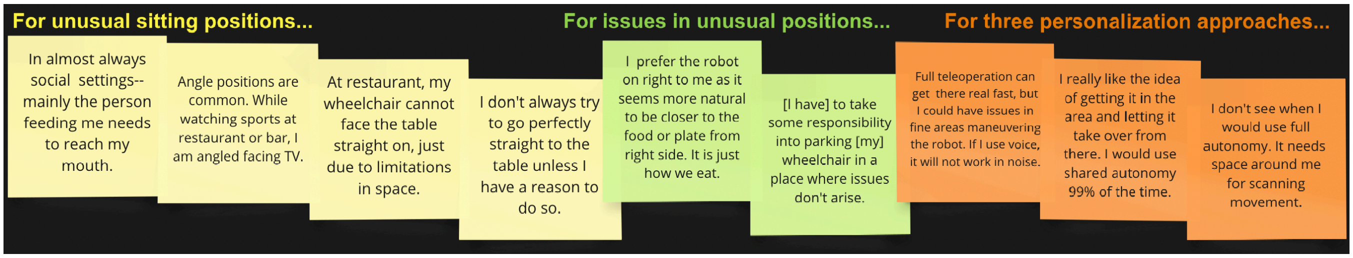

Figure 3: Qualitative data analysis in Miro.

3.3 Methods

We interviewed the participant to gauge his experiences and opinions about his eating environment, our RAF system, and preferred interaction medium for ADA. For survey questions on his experiences of eating and using assistive technology, see Appendix A.1. To get feedback on personalization approaches, we first showed the participant simulated videos[2] and then asked him questions listed in Appendix A.2. While showing the videos, we verbally explained how the user would control the robot using our UI (see Fig. 1(b)). The user would direct the robot using the directional buttons of the UI. That is, the user can click on one of four cardinal directional buttons to direct the robot arm to move forward, backward, right, and left, in a plane over the table. The user keeps clicking on the UI buttons until full and partial plate views are located in FT and SA, respectively. For full plate views, the plate should be approximately centered in the camera frame. For partial plate views, some part of the plate should be visible in the camera frame. In SA, locating the full plate from the partial plate view is dependent on the visual servoing algorithm. The key difference between FT and SA is that in FT the users will press app buttons until locating the full plate, whereas in SA the users direct the robot to a partial plate view, and then the robot takes over for locating the full plate. In SA, users will be alerted through the app when the partial plate has been located and it is time for the robot to take over switching from user input. In FA, the user never uses the UI and the robot does everything automatically. In this case, the robot arm will scan the table until it finds part of the plate, then center the plate in the camera frame.

The participant was interviewed by the first three authors of this paper during the study. There were follow-up questions asked from both the interviewee's and interviewers' sides to gain further clarity on topics raised and discussed. Our presented methods are approved by the University of Washington IRB under protocol #IRB-0001-4869.

We conducted a transcription-based analysis on the interview data to filter for the key quotes of the study participant (see Fig. 3) using Miro[3]. Our transcription provided us with valuable insights into the qualitative data from the study and the user feedback on the personalization approaches. We also conducted a thematic evaluation of those approaches based on our discussion with the study participant (see Table 1).

3.4 Preliminary Results

The study participant often sits in angular, parallel, and forward-facing positions while eating (see Fig. 4). Occasionally, the height

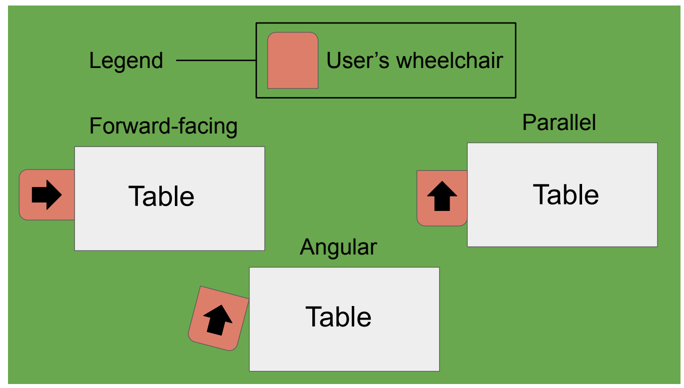

Figure 4: Sitting positions stated by the study participant.

of the table limits his seating choices as low tables may not have enough leg space for him to sit in a forward-facing position. In social settings (e.g. restaurants), when watching TV, or getting fed by a caregiver, he often sits at an angle or in parallel to accommodate the comfort of others (see Fig. 3). Responses from this first test viewer reveal anecdotal insights (see Fig. 3) about our personalization approaches. This participant mentioned some pros and cons of all three approaches. As pros of **FT**, he mentioned *speed* stating *"I can get the robot in the vicinity of everything quickly."* For cons, he shared concerns about the detailed movements necessary to center the plate: *"Let's say I can't move it. I have my issue with really fine areas maneuvering my robot."* He also shared that if he uses voice to interact with ADA's UI (see Fig. 1(b)), he might fail to control the robot with FT in a noisy environment. **For SA, he mentioned *"I really like the idea of getting it in the area and letting it take over from there. That's something I would use 99% of the time."*** He expressed one concern about SA: *"If it takes more than 30 seconds for the robot to automatically take control, I would just like to locate it myself."* He also suggested an alternative: *"Maybe have a button in the UI to tell the robot when to take control."* This is an option for future work; however, having a button to manually click rather than an automatic process might increase user dependency and intermediate delay. For pros of **FA**, he mentioned *"It allows me to not having to think and multitask."* For the cons of this approach, he shared *"I need adequate space around me for its scanning movement."* We discussed that if the scanning movement was random or unaware of its environment, it could run the risk of damaging the arm or other objects in the environment.

The participant gave the highest ranking to SA, noting that it was the preferred system. From the study data, we selected "robustness", "speed", "effort", and "multitasking" as the four key themes needed from the user's perspective for personalizing RAF systems.

[2]Simulated videos for locating the plate in ADA: https://youtu.be/7Br3Y1NRbAo
[3]Miro: https://miro.com/

Table 1: Thematic evaluation of three personalization approaches.

Theme	Full Teleoperation (FT)	Shared Autonomy (SA)	Full Autonomy (FA)
Robustness	✗	✓	✗
Speed	✗	✓	✗
Effort	✗	✓	✓
Multitasking	✗	✓	✓

While analyzing the interview data, we looked for common patterns that came across as the decision-making factors behind the pros and cons of each approach to select these themes: robustness (the ability to guarantee performance in different environments), speed (the ability to complete the task faster), effort (the ability to save user effort), and multitasking (the user's ability to perform other actions, such as carrying on a conversation, while the task is completed). The checkmarks in the table represent whether the study participant found the approach to fulfill his requirements for each theme. Here, we analyze each method according to these themes.

Robustness: FT may not work if voice control is used in noisy environments. SA may be impacted as well, although its impact may be less severe as only a few movements should be needed to find a partial view of the plate. FA requires knowledge of the environment or fine-tuned obstacle detection, which may not hold in certain environments; for example, a clear glass of water may be difficult to avoid.

Speed: The speed of FT greatly depends on the skill of the user operating the arm. As the plate needs to be fully centered, this process may take some time. SA can be faster than FT as the user only needs to direct the robot to a partial plate view. The speed of FA may vary greatly based on how much of the surrounding area it needs to scan in order to find the plate.

Effort: FT saves no user effort, as the entire process is teleoperated by the user. FA saves all user effort, as the entire process is automated. SA strikes a balance between these two modes. SA saving partial human effort might be better than saving all effort as users actually gain satisfaction by giving effort into a system that is not very demanding [5].

Multitasking: FT does not allow multitasking as the user will be occupied during the entire task. SA allows partial multitasking during the automated part of the task. FA allows the most multitasking, as no user input is needed.

As shown in Table 1, SA is the only one among our three personalization approaches that satisfies (or partially satisfies) all of these four key themes. FT and FA do not satisfy all four themes, although they do have scenarios in which they may outperform or be preferable to SA. Following the thematic analysis, we rank SA as the first, FA as the second, and FT as the third preferred approach.

4 DISCUSSION & FUTURE WORK

This case study results support our hypothesis that SA may be preferred to adapt to unforeseen sitting positions in RAF. These findings also support other investigations into shared autonomy that were not directly applied to customizing RAF systems [1–3, 7–9]. SA can also help with other issues of RAF systems, such as adjusting the robot's movement to accommodate various heights of tables or wheelchairs, or adapting to the user's preferred manner, speed, and pauses in food delivery [13, 14]. SA adds balanced autonomy to human settings. As a user gradually gets used to the teleoperation patterns needed for specific positions, the amount of teleoperation may be reduced for the common patterns learnt over time. The robot can also learn from humans (e.g., save teleoperation patterns for specific tasks or locations) in SA, and then perform autonomously using that learning in an FA algorithm. This learnt FA approach should gain robustness for all use cases as learnt over time. Thus, such FA may become preferable to SA over time with each user. This will be faster and rescue users from doing the same operation each time. Such applications may involve methods like reinforcement learning, learning from demonstration, and lifelong learning.

We acknowledge some shortcomings of this work. First, the study involved only one human participant and one task. In future work, we plan to test out levels of autonomy with more users and tasks to determine when SA, FA, and FT are best utilized. Second, a plate locator algorithm was not yet implemented on ADA, so the participant was shown demonstrations of ADA with different autonomy levels rather than actually interacting with the system. We plan to implement both SA and FA (top two from Table 1) in ADA to have them available during a long-term deployment study. We plan to track how long it takes for each of them in real-time control and how well they personalize to the user(s) fulfilling the themes from Table 1 and other practical constraints. We also intend to test out SA and FA in different tasks outside of locating plates in the future. There may be issues in acquiring and transferring the bite due to unusual positions, different heights of the table and the wheelchair, presence of other objects and people in the eating environment (see Fig. 3). Knowing concrete success and failure areas of these experimental results will enable more desirable and robust use of different autonomy levels for long-term and personalized HRI settings.

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REFERENCES

[1] Reuben M. Aronson, Thiago Santini, Thomas C. Kübler, Enkelejda Kasneci, Siddhartha Srinivasa, and Henny Admoni. 2018. Eye-Hand Behavior in Human-Robot Shared Manipulation. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction (Chicago, IL, USA) (HRI '18). Association for Computing Machinery, New York, NY, USA, 4–13.

[2] Tapomayukh Bhattacharjee, Maria E. Cabrera, Anat Caspi, Maya Cakmak, and Siddhartha S. Srinivasa. 2019. A Community-Centered Design Framework for Robot-Assisted Feeding Systems. In Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility (Pittsburgh, PA, USA) (ASSETS '19). Association for Computing Machinery, New York, NY, USA, 482–494.

[3] Tapomayukh Bhattacharjee, Ethan K. Gordon, Rosario Scalise, Maria E. Cabrera, Anat Caspi, Maya Cakmak, and Siddhartha S. Srinivasa. 2020. Is More Autonomy Always Better? Exploring Preferences of Users with Mobility Impairments in Robot-Assisted Feeding. In Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction (Cambridge, United Kingdom) (HRI '20). Association for Computing Machinery, New York, NY, USA, 181–190.

[4] Gerard Canal, Guillem Alenyà, and Carme Torras. 2016. Personalization Framework for Adaptive Robotic Feeding Assistance. In Social Robotics, Arvin Agah, John-John Cabibihan, Ayanna M. Howard, Miguel A. Salichs, and Hongsheng He (Eds.). Springer International Publishing, Cham, 22–31.

[5] Gerard Canal, Carme Torras, and Guillem Alenyà. 2021. Are Preferences Useful for Better Assistance?: A Physically Assistive Robotics User Study. ACM Transactions on Human-Robot Interaction 10, 4 (Dec. 2021), 1–19.

[6] Daniel Gallenberger, Tapomayukh Bhattacharjee, Youngsun Kim, and Siddhartha S. Srinivasa. 2019. Transfer Depends on Acquisition: Analyzing Manipulation Strategies for Robotic Feeding. In Proceedings of the 14th ACM/IEEE International Conference on Human-Robot Interaction (Daegu, Republic of Korea) (HRI '19). IEEE Press, 267–276.

[7] Siddarth Jain and Brenna Argall. 2019. Probabilistic human intent recognition for shared autonomy in assistive robotics. ACM Transactions on Human-Robot Interaction (THRI) 9, 1 (2019), 1–23.

[8] Shervin Javdani, Henny Admoni, Stefania Pellegrinelli, Siddhartha S Srinivasa, and J Andrew Bagnell. 2018. Shared autonomy via hindsight optimization for teleoperation and teaming. The International Journal of Robotics Research 37, 7 (2018), 717–742.

[9] Hong Jun Jeon, Dylan P Losey, and Dorsa Sadigh. 2020. Shared Autonomy with Learned Latent Actions. In Proceedings of the 2020 Robotics: Science and Systems Conference (Corvalis, Oregon, USA).

[10] Min Kyung Lee, Jodi Forlizzi, Sara Kiesler, Paul Rybski, John Antanitis, and Sarun Savetsila. 2012. Personalization in HRI: A Longitudinal Field Experiment. In Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction (Boston, Massachusetts, USA) (HRI '12). Association for Computing Machinery, New York, NY, USA, 319–326.

[11] Rishabh Madan, Rajat Kumar Jenamani, Vy Thuy Nguyen, Ahmed Moustafa, Xuefeng Hu, Katherine Dimitropoulou, and Tapomayukh Bhattacharjee. 2022. SPARCS: Structuring Physically Assistive Robotics for Caregiving with Stakeholders-in-the-loop. In IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2022, Kyoto, Japan, October 23-27. IEEE, 641–648.

[12] Amal Nanavati, Patrícia Alves-Oliveira, Tyler Schrenk, Maya Cakmak, and Siddhartha S. Srinivasa. 2023. Design Principles for Robot-Assisted Feeding in Social Contexts. In Proceedings of the 18th ACM/IEEE International Conference on Human-Robot Interaction (Stockholm, Sweden) (HRI '23).

[13] Daehyung Park, Yuuna Hoshi, Harshal P. Mahajan, Ho Keun Kim, Zackory Erickson, Wendy A. Rogers, and Charles C. Kemp. 2020. Active Robot-Assisted Feeding with a General-Purpose Mobile Manipulator: Design, Evaluation, and Lessons Learned. Robotics and Autonomous Systems 124, C (Feb 2020), 17 pages.

[14] Lorenzo Shaikewitz, Yilin Wu, Suneel Belkhale, Jennifer Grannen, Priya Sundaresan, and Dorsa Sadigh. 2023. In-Mouth Robotic Bite Transfer with Visual and Haptic Sensing. In IEEE International Conference on Robotics and Automation (ICRA) (London, UK) (ICRA '23).

[15] Catarina Silva, Jayakorn Vongkulbhisal, Manuel Marques, João Paulo Costeira, and Manuela Veloso. 2017. Feedbot - A Robotic Arm for Autonomous Assisted Feeding. In Proceedings of the Progress in Artificial Intelligence: 18th EPIA Conference on Artificial Intelligence (Porto, Portugal) (EPIA 2017). Springer-Verlag, Berlin, Heidelberg, 486–497.

A SURVEY QUESTIONS

A.1 Experiences of eating and assistive technology

- **Q1:** Could you tell us about your experiences when you are unable to sit forward facing a table while eating, and perhaps you need to sit at a different way (e.g., in an angle)?
- **Q2:** What issues do you think can arise when you are using ADA for eating assistance in these different (e.g., angular) positions and how to overcome those?
- **Q3:** Could you please tell us about the plates you use for eating? Like, if you could tell us about the colors, patterns or shapes and materials of the plates you typically use?
- **Q4:** Could you please tell us about the table you typically use for eating? What are the properties of table(s) like color and material? Also, is there typically just one plate there, or are there other objects (e.g., napkins, other plates, etc.)? Are there many objects on the table obstructing plates and food items, or presence of other objects apart from plates and food?
- **Q5:** How is your usual eating environment beyond the table (e.g., wall, cabinets)? Do you eat in the same location or does it change?
- **Q6:** Which assistive technology you use to interact with phone, and how that assistive technology works through your phone?

A.2 Personalization approaches in ADA

- **Q1:** What pros and cons do you see in using full teleoperation, shared autonomy, and full autonomy approaches for locating your full plate in ADA-assisted feeding?
- **Q2:** Is there any feedback you would like to share to improve our UI design (see Fig. 1(b)), or full teleoperation, shared autonomy, and full autonomy approaches to best serve your needs in robot-assistive feeding?
- **Q3:** Could you please rank these 3 approaches? Will your ranking change based on circumstances?
- **Q4:** Among these 3 approaches discussed, which approach you prefer most and why? Do you think there is a clear winner?