Is More Autonomy Always Better? Exploring Preferences of Users with Mobility Impairments in Robot-assisted Feeding

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ABSTRACT

A robot-assisted feeding system can potentially help a user with upper-body mobility impairments eat independently. However, autonomous assistance in the real world is challenging because of varying user preferences, impairment constraints, and possibility of errors in uncertain and unstructured environments. An autonomous robot-assisted feeding system needs to decide the appropriate strategy to acquire a bite of hard-to-model deformable food items, the right time to bring the bite close to the mouth, and the appropriate strategy to transfer the bite easily. Our key insight is that a system should be designed based on a user's preference about these various challenging aspects of the task. In this work, we explore user preferences for different modes of autonomy given perceived error risks and also analyze the effect of input modalities on technology acceptance. We found that more autonomy is not always better, as participants did not have a preference to use a robot with partial autonomy over a robot with low autonomy. In addition, participants' user interface preference changes from *voice control* during individual dining to *web-based* during social dining. Finally, we found differences on average ratings when grouping the participants based on their mobility limitations (lower vs. higher) that suggests that ratings from participants with lower mobility limitations are correlated with higher expectations of robot performance.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in accessibility**; • **Social and professional topics** → **People with disabilities**; **Assistive technologies**; • **Computer systems organization** → **Robotic autonomy**.

KEYWORDS

Assistive Feeding, Assistive Robotics

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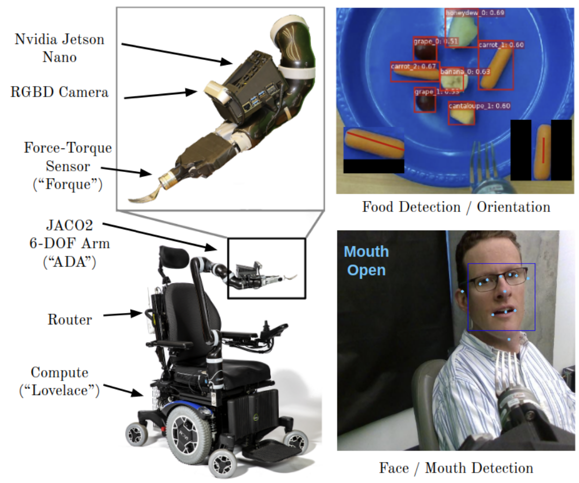

Figure 1: Our robot-assisted feeding system, ADA, with a JACO robotic arm mounted on a Rovi wheelchair. The robot-arm is equipped with an eye-in-hand camera system and it holds a fork instrumented with a 6-axis F/T sensor using a custom 3D-printed holder. The system detects different food items on a plate and finds the best action for bite acquisition as well as detecting the face and whether the mouth is open for bite transfer.

1 INTRODUCTION

Nearly 190 million people in the world live with some form of motor impairment, according to the World Health Organization. Motor limitations have been associated with required assistance performing activities of daily living (ADLs), such as eating, bathing, and dressing [33]. The need for constant specialized care creates a large financial burden, while perceived loss of independence introduces mental health challenges for individuals with impairments [43].

Robots have the potential to increase or prolong unassisted living for people with mobility impairments by facilitating ADLs. Enabling autonomous ADL assistance is a long standing goal of robotics research focusing on tasks such as food manipulation and feeding [32], personal hygiene [34], fetching objects off the floor [25], or handing items off to people [58]. Despite great strides taken towards sustainable solutions, autonomous products are far from ready for adoption due to the frequency and severity of possible errors introduced through automation. While full autonomy may be a decade away, many users could benefit from partial solutions now.

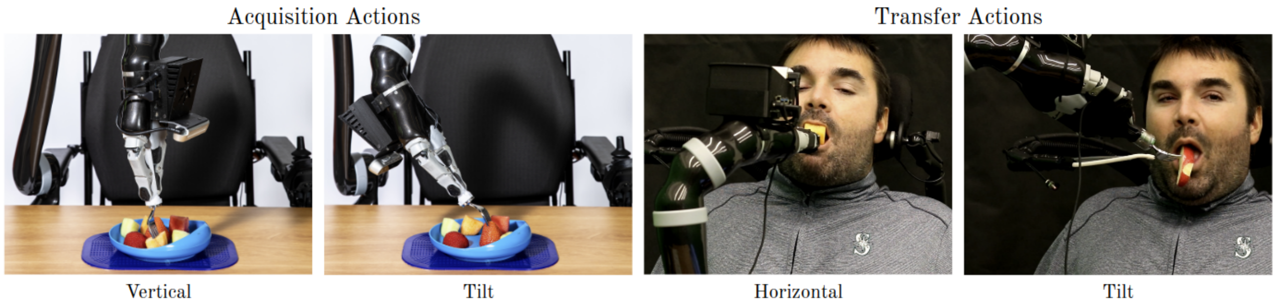

Figure 2: Action options available to the robot: *Left:* Two bite acquisition actions, *Right:* Two bite transfer actions.

Semi-autonomous systems, which trade-off autonomy for greater user-control, are one approach to overcome the hurdles introduced by automation errors. Specifically, the challenging parts of the task may be left to humans, while the more robust robot functions remain autonomous. Although we might be able to achieve functional semi-autonomous systems much faster than fully-autonomous ones, they present a different challenge for users with mobility limitations. Semi-autonomy requires more input from users to control the robot, which may be difficult to provide given the limited input bandwidth of assistive input devices. Hence, there is a tension between making robots more autonomous (introducing possible errors) and making them more user-controlled (more user input and effort). It is unclear what real users of assistive robots prefer in terms of autonomy, given this tension, and what factors might impact these preferences.

In this paper we explore end-user preferences for different autonomy levels and investigate the impact of challenges associated with automation errors and need for user input, in the context of robot-assisted feeding. We present two studies in which 10 individuals with varying mobility limitations came to our lab to interact with a wheelchair-mounted robotic arm programmed for assistive feeding (see Fig. 1). Participants were fed food items with different versions of the robot to elicit their preferences and gather feedback. In the first study, we explored challenges associated with different input modalities (speech and web-based) and different robot feeding speeds in individual or social dining scenarios. We found that participants prefer voice interface during individual dining but the ratings for web-interface go up for social dining scenarios. In the second study, we investigated user preferences for autonomy levels by comparing a low-autonomy robot that requires user input for different aspects of feeding, with versions of the robot where the need for input is removed partially through automation. Users did not have a clear preference towards more autonomy. We demonstrated different error types introduced by automation to understand user tolerance to such errors. We also analyzed user preferences based on their range of mobility limitations, and found that users with lower mobility limitations had higher expectations of robot performance when compared to people with higher limitations. We replicated this study online, through videos with an actor, reaching 8 additional participants. We found that people may prefer the least amount of autonomy despite the extra effort required, especially when the expected frequency of certain automation errors are high but the current experiment did not find any statistically significant differences.

2 RELATED WORK

While specialized feeding devices for people with disabilities have been introduced on the market [1–5, 7, 9, 10, 13], they lack widespread acceptance. Numerous researchers have also developed robot-assisted feeding systems, either as table-mounted robotic arms [24, 36, 39, 40, 44, 49, 52, 53, 55, 57, 59, 60, 62, 63, 65, 67, 68], general purpose mobile manipulators [20, 50, 54], or wheelchair-mounted robotic arms [16, 21, 28, 30, 32, 37, 45]. A comprehensive review of meal assistance robots is given in [22, 42, 47, 61]. Some assistive systems focus more on support or adaptation to the user. For example, several emphasize tremor cancellation during the feeding task [12, 48, 51], while others provide arm support for users who can move their arm but do not have sufficient muscular strength for continued large movements [11, 14, 64]. Among some of the developed assistive feeding systems based on autonomous robots, Park et al. [50] used a general purpose manipulator to scoop yogurt with a spoon communicating with the user via a web interface. Ettehadi and Behal [29] used learning from demonstration to learn scooping trajectories for robotic feeding. Other examples of robotic systems which can skewer solid food items with a fork are Herlant [35], who also explored modeling an intelligent bite-timing model in social dining scenarios, and Gallenberger et al. [32], who developed a system that can detect a solid food item specified by a user and pick it up autonomously. Both these studies did not develop an explicit user-interface and did not test the system with people with mobility impairments. Also notable is the work by Canal et al. [23], who developed an intelligent personalization framework for robot-assisted feeding systems that can adapt to user preferences.

Full autonomy, as attempted by the studies above, comes with various challenges. As studied in [18], using a 10-point taxonomy for categorizing robot autonomy levels, there are various levels of robot autonomy which may be appropriate in different scenarios. Kim et al. [41] discussed how autonomy impacts performance and satisfaction for users with Spinal Cord injuries. They looked at full teleoperation mode to full autonomy mode without any errors in pushing and reaching tasks. Javdani et al. [40] looked at shared autonomy when compared to direct teleoperation and full autonomy for the bite acquisition of marshmallows. However, there is hardly any work on analyzing the effect of autonomy with perceived error risks and variables such as robot speeds and interfaces on robot-assisted feeding systems for user acceptance. This work aims towards closing this gap by exploring multiple variables and analyzing the effect of perceived error risks on robot autonomy.

3 SYSTEM OVERVIEW

3.1 The Robot

Our setup, the Autonomous Dexterous Arm (ADA), consists of a 6 DoF JACO 2 robotic arm [38], mounted on a powered ROVI wheelchair [6] to mimic similar setups used in real homes. The arm has 2 fingers that grab an instrumented fork (forque) using a custom-built, 3D-printed fork holder. The system uses visual and haptic modalities to perform the feeding task. For haptic input, we instrumented the forque with a 6-axis ATI Nano25 Force-Torque sensor [56]. We use haptic sensing to control the end effector forces during skewering. For visual input, we mounted a custom built wireless perception unit on the robot's wrist; the unit includes the Intel RealSense D415 RGBD camera and the NVidia Jetson Nano for wireless transmission. Food is placed on an assistive plate mounted on an anti-slip mat commonly found in assisted living facilities.

We implemented three levels of safety in our system. First, a tight collision box is positioned around the user's face to ensure collision avoidance. We have also implemented a low force threshold on the instrumented fork and the robot behaviors are designed such that it will stop the moment it touches anything on its way to the face. Finally, we have an operator sitting close to the robot throughout the experiment who can stop the robot if unwanted behavior is detected.

3.2 Modes of Feeding: Autonomy and Speed

Our robotic system can switch between different modes of operation. For speed, our robot arm can move in either the slow setting (0.2 rad/s for each joint during most motions, 0.1 rad/s for each joint during approach to face) or in fast setting (0.8 rad/s for each joint during most motions, 0.2 rad/s for each joint during approach to face). For autonomy, once a food item is selected by the user, our robot can function in any of the following modes:

Full Autonomy - FA. : At the start of a fully autonomous feeding trial, the user can select a specific food item on a plate or have the robot choose one randomly using an interface. The robot arm moves to a pre-determined configuration above the plate facing down to see the entire plate using the wrist-mounted camera. Depending on what food item the user selects, it perceives the food items on the plate using perception algorithms [31] and decides what is the best strategy to pick up the one selected. Once the algorithms determines the strategy, the robot arm servoes to it using feedback from the visual modality, acquires the bite using feedback from the haptic modality [20], and then moves up to a pre-determined configuration to perceive the user's face. The robot detects the user's intent to eat when it perceives the user's mouth open using the wrist-mounted camera, which is facing the user sitting on the wheelchair. This is based on our initial discussions when the caregivers mentioned that they look for the mouth-open cue to determine when to approach to feed the care-recipients [19]. Once the robot detects the 3D position of the face and sees the mouth open, it approaches. The robot-arm then determines the best strategy [31] to feed the food item on the fork so that it is easy for the person to take a bite. Once the robot-arm has reached its final position, it communicates to the user that the food is ready to eat and the user takes a bite. The robot waits for a fixed duration of

Figure 3: Participants with mobility impairments with options for the voice interface using Alexa and web-interface displayed in their/our tablets mounted in different positions according to their preference or constraints of system integration. When needed a switch was installed to control the web interface.

time. The feeding trial ends once the robot moves away from the mouth and goes back to its home position.

Low Autonomy - LA. : Similarly to FA, the feeding trial starts with a user selecting a food item. The robot then moves to a pre-determined configuration above the plate to see the plate and perceives the food item on the plate using perception algorithms [31]. However, instead of selecting the best pick-up strategy by itself, it asks the user to choose an action to acquire the food item. Since this study only deals with solid fruit pieces, there are two options available to the user: *vertical* and *tilted* skewering, as shown in Fig. 2. Once the user selects one option, the robot performs the action and picks up the food. Then, it moves to the pre-determined configuration to focus on the user's face. The robot then asks the user to select the best strategy to transfer the food item to their mouth and when to feed them. There are two options for choosing a strategy for transferring a bite: *horizontal* and *tilted* transfer. Once a user selects a transfer strategy and asks the robot to feed, the robot approaches the person's mouth. Once the robot has reached its final position, it communicates to the user that the food is ready to eat and the user takes a bite. The feeding trial ends with the robot moving away from the mouth and returning to its home position for next trial.

Partial Autonomy - PA:. : In partial autonomy mode, we maintain any one of the three phases of feeding autonomous while the rest are non-autonomous. In the *autonomous acquisition - AAc* mode, the bite acquisition phase is autonomous and the robot decides the best strategy to pick up the food item that the user selected using its algorithms [31]. In the *autonomous timing - ATi* mode, the bite timing phase is autonomous and the robot decides when to approach the user's face based on whether the mouth is open or not. Detecting the face and whether the mouth is open or not is not trivial choice for automation given the different angles in which

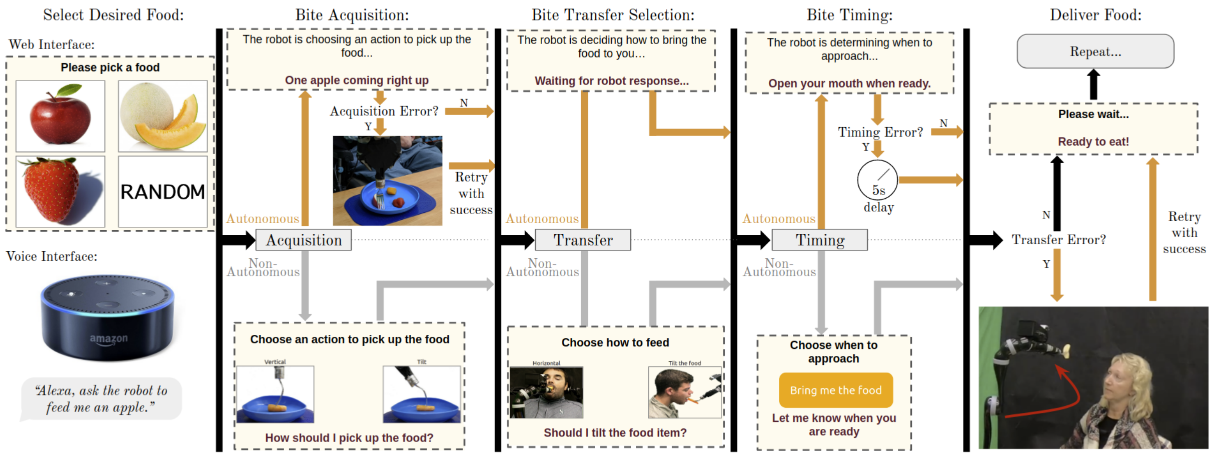

Figure 4: Each phase of interaction and error recovery is depicted as a column in the system flow chart. Orange arrow branches indicate flow under the *autonomous* condition for each phase while gray arrow branches indicate *non-autonomous*. Each dashed box shows what the user sees on the web GUI, depending on the phase condition. The dark red text in each yellow box indicates the robot's current status. In the 'voice interface' condition, the robot speaks the red text rather than displays it.

the faces are oriented for this target population as well as possible occlusion from the food on the fork itself. In the *autonomous transfer - ATr* mode, the bite transfer phase is autonomous and the robot decides the best strategy to transfer the food item that the user selected using its algorithms [31] during bite transfer.

3.3 User Interfaces

We provide two interface variants to the users: bi-directional voice and bi-directional web GUI (see Fig. 3). Both of these interfaces follow the same procedural flow shown in Fig. 4. The bi-directional voice interface uses the Amazon Echo Dot and the Alexa Voice Service (AVS) [8] as a backend. We made this design decision to ensure the voice models would scale with state-of-the-art performance provided by AVS. Each command given to the robot requires: 1) Invoking Alexa to listen by uttering the hotword *"Alexa"*, 2) specifying the corresponding Alexa skill by uttering *"ask the robot to"* and 3) giving a command. A full utterance might look like: *"Alexa, ask the robot to feed me an apple."*. The voice model detects the words in the command and fits them to a grammar from which our system extracts the salient information.

We also give each user the ability to visit the web GUI via their personal tablet device, allowing interaction through their preferred adaptive button or touch input. If the user does not have their own personal device, we provide a stand-mounted tablet adjacent to the plate of food. The user interacts with this tablet via a specialized button [15] they can press with minimal movement.

4 STUDY 1: ROBOT INTERFACES / BEHAVIORS IN DIFFERENT CONTEXTS

Dining together with other people is a cornerstone of society and provides a personal link to the wider community [27, 46, 66]. Dining habits have a particularly high impact on the morale of those with disabilities. Hence, we are interested in exploring user preferences when different social contexts are considered during feeding: scenarios where the user would be dining individually or socially. This study is aimed to gather the preferences of target population on some of the design parameters considered for the robotic feeding system such as the robot's input/output modality and the execution speed.

4.1 Methods and Procedures

We tested two different values for each of the design parameters in two dining scenarios. For speed, we used the *slow* and *fast* setting. For interface, we used *voice* and *web*. The input and output information for the interfaces were the same, just the modalities were different. We tested all combinations of these parameters for both *individual* and *social* dining scenarios.

The study was conducted with the approval of our university's Institutional Review Board (IRB). Before scheduling each participant, we provided an initial recruitment questionnaire that confirmed if the participants identified as people with mobility impairments and if they currently used a power wheelchair. We collected details relevant to the design of our experiment: confirming they could use both selected interfaces (*voice* and *web*), any food allergies to determine what items to include, and how to acquire consent.

We selected three fruits that the robot would feed the participants during the experiment: 1) apples, 2) strawberries, and 3) cantaloupes. We selected a limited number of items to reduce uncertainty in perception and manipulation, as those factors are outside the scope of this particular study.

Due to challenges related to transferring the participants from their wheelchairs to our robot-on-wheelchair system, a modification to the system was introduced. The participants' comfort in their customized chairs was of paramount importance, given that they would spend a long period of time in our laboratory. Mounting the robotic arm on each participant's chair was also challenging given different mounting requirements for different wheelchairs. Hence, the robotic arm was mounted on a tripod at the same height of where it would be mounted on the wheelchair. In a real home environment for long-term use, the robot arm would be mounted in their wheelchairs with all the required customizations.

Figure 5: Two scenarios: *Left:* Individual dining, *Right:* Social dining.

Once the participants came to the laboratory, we went over the consent form together with the caregiver. We then asked the participants to position their wheelchair facing the table. We positioned the tripod near the wheelchair and based on this, we re-calibrated the experimental setup. There was an initial setup time in our experiment where the participants familiarized with the use of both interfaces. All participants required different accommodations in terms of using their or our own devices to display the web interface, as well as setting up a *Tecla* device and a scanning/switch button on their wheelchair to navigate and select in the web interface. The initial setup finished going through the study protocol with both the participant and their caregivers, as well as the safety measures.

We designed this study to have 4 trials in each dining scenario, individual and social, both shown in Fig. 5. Trials combining different speed and interface selections were presented randomly for each participant. After each trial, we administered a questionnaire which asked them to provide ratings for the trial they just saw. In the individual dining scenario, the robot fed the user individually whereas for the social dining scenario, we asked the caregivers to accompany the participants during the feeding trials and engage in normal conversations as they would, when eating together. In the social dining scenario, we provided the caregivers the same food items as we did for the participants.

For all the feeding trials, the robot ran in *fully autonomous* mode (See Section 3.2) in which the participants communicated the robot what food items they wanted during a particular trial and then the robot autonomously performed the feeding task. We designed the study so that for every trial, there was exactly one piece of a particular food item on the plate and when it was eaten, we replenished that particular food item. Note, the participants were never forced to eat a food item but we did request them to take the bite off the fork to complete the feeding process and then later discard the food item if they chose to do so. After each trial, the participants were asked questions about their preferences of robot speed, user interface and general technology acceptance questions based on the TAM model [26]. At the end of the experiment, the participants answered a final *post-task questionnaire* which included some demographics questions as well as some semi-structured and open-ended questions about their general experience with the system.

4.2 Participants

For this study, we recruited ten participants, eight male and two female, between the ages of 28 and 57. We provide some details on their type of mobility impairment in Table 1 and the modifications made to the experimental setup to facilitate their participation.

Table 1: Participants self-reported mobility limitation description and grouping based on mobility (lower (L) vs higher (H) mobility limitation)

Participant	Age	Self-reported mobility limitation	Group
P1	34	C1 quadriplegia	H
P2	38	C2 quadriplegia	H
P3	57	C5-C6 complete	L
P4	40	Arthrogryposis	L
P5	31	C1 tetraplegia	H
P6	33	C1 tetraplegia	H
P7	37	C1-C2 quadriplegia	H
P8	28	C3-C4 quadriplegia	H
P9	45	C4 incomplete	L
P10	38	C4-C5 complete	L

Given the range of mobility limitations in the participant pool, we grouped participants based on it: six of the participants showed higher mobility limitations and the remaining four showed lower mobility limitations. Mobility level was also considered as a factor while evaluating their responses and ratings to the system.

Two of our higher mobility limitation participants had little to no neck movement. This required an additional calibration of the system to the final phase of food transfer to occur inside their mouth. These participants used devices controlled by sip and puff. Depending on their mobility limitation, some participants used a push button with their heads, or used their own arms while grasping a tool to touch the tablet's screen.

Some of our participants were more proficient with technology than others. One of the participants was an expert Tecla user with access to a Kinova arm with no autonomy features. This participant shared his experience of teleoperating the robot (fully non-autonomous) to pick one piece of fruit and bring it to his mouth would take him approximately 45 minutes. Other participants did not use a particular electronic device with assistive features, so they had to familiarize themselves with the one provided in the lab.

4.3 Findings

A General Linear Model was fitted using *Speed*, *Interface*, and *Mobility* as main factors with the data split for Individual and Social environments. Interactions between factors were found non-significant for all dependent variables. The mobility factor was found significant only on TAM responses, as shown in Fig. 6: users with higher limitations gave higher scores to the average of all TAM responses ($p = 0.05$) in the individual dining scenario, to attitudes towards the system (ATT, $p = 0.03$) in the social scenario, and to perceived usefulness (PU) in both individual ($p = 0.031$) and social ($p = 0.039$) dining scenarios.

Participants may prefer faster speeds for potential use but may feel safer with slower speeds with diverted attention. Fig. 7 shows the results. The current experiment did not find any statistically significant differences in speed options. There were however some trends worth mentioning: in the individual dining scenario, all speed preference responses show the faster speed as the preferred option, including the question about *feeling safe*; however, in the social dining scenario the difference in ratings for all responses are reduced, with the safety responses switching trend to preferring lower than faster speeds. This may be confounded

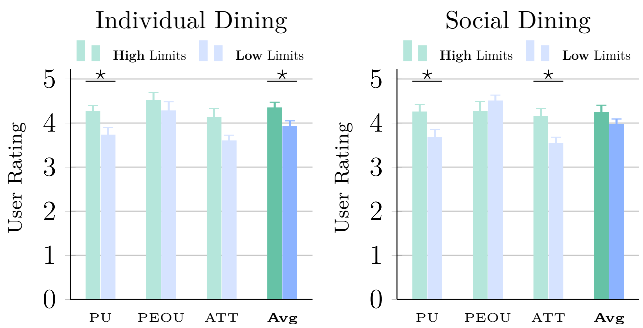

Figure 6: Grouping based on mobility limitations was found significant as a factor for differences in TAM responses for individual and social dining scenarios.

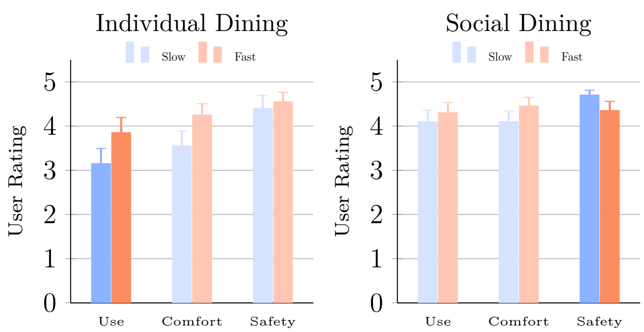

Figure 7: User ratings on speed preferences for each dining scenario. No statistical significance was found between slow and fast speed settings. Among notable trends, safety rating preference switches from fast in individual dining to slow in social dining.

by the fact that the participants were engaging in conversation in the social scenario and were not focusing all their attention on the robot moving towards them.

This is further bolstered by the participants' comments gathered during the post task questionnaire. One of P3's major points of contention about the robotic system was regarding the robot's speed: "The speed was good when it was coming towards me, but selecting and picking was slow". One of P1's suggestions regarding potential modifications to the system before it is used in their homes was finding a way to "... for the users to change speed easily. Everyone feeds themselves in life at different speeds". This was also highlighted by P4 during the post task questionnaire, mentioning that the fast setting still did not cause any alarm for him: "I think it's always good to shoot for faster speeds, there weren't any fast speeds that were fast enough to cause me any alarm"; however, there were slower ones that "I wouldn't want in my daily life" (P4).

Participants prefer voice to web when dining individually but prefer web over voice when dining socially. Fig. 8 shows the results. The *interface* factor was found significant in both dining scenarios. During individual feeding, participants gave higher scores to the *voice* interface in all questions ($p < 0.001$) regarding interface except the prompt about *enough information.* Conversely, during the social dining scenario, participants gave higher scores to the *web* interface in all questions except the prompt about choosing to *use this robot* ($p < 0.05$).

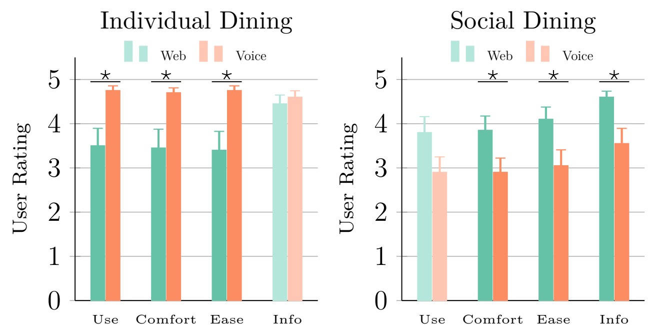

Figure 8: Dining scenario affects the choice of interface. Voice was rated statistically higher than web in individual dining. Conversely, statistical significance was found for web over voice in the social dining scenario.

Among the reasoning behind interface rating during the feeding trials, P2 stated that in the social scenario the voice interface was interrupting and made it more difficult to carry a conversation whilst P4 stated "I liked that I could just tell it what I wanted and we could continue having a conversation". Moreover, there was no agreement with the use of the web interface in social setting. P1 and P2 were comfortable using the web interface, P2 said he could "carry a conversation", while P3 considered it "too distracting during conversation" and P4 said that the web interface was less disruptive in some ways although "kind of gets physically in the way with the social interaction. But it is good that it doesn't interrupt us talking".

Participants agree to the technology's perceived acceptance and usage. Participants, in general, liked our robotic system. P1 mentioned "What entices me about the robot is being able to give one command and have the robot bring me the food (...) I want (to give) one command and then I want the robot to decide everything else (...) but what I do want to control is the speed". P2 added "There is a remarkable amount of independence with this (...) I like to be able to (eat) by myself". P3 also said "Sometimes I wanna eat by myself and be by myself. I don't feel like I have to talk and just be quiet and eat quietly and independently without anyone around. That part I like".

5 STUDY 2: ROBOT AUTONOMY GIVEN PERCEIVED ERROR RISKS

It is inevitable that an autonomous robotic system will have errors when used in real-life for long term. We designed the study to see the participants' autonomy preferences with perceived error risks by deliberately introducing errors in some of the autonomous trials. We designed the study such that in trials with errors, the robotic system recovered from the error autonomously after one try.

5.1 Methods and Procedures

For this study, the experimental setup and the pool of participants were the same as that of the previous study described in Section 4. Additionally to our in-person participants, we gathered responses from 8 additional participants using a video questionnaire, where an actor was used to showcase the different autonomous modes and the associated errors in multiple feeding trials. Online participants' age range was between 25 - 77 years, 7 male and 1 female, with mobility impairments like spinal cord injuries, loss of strength in

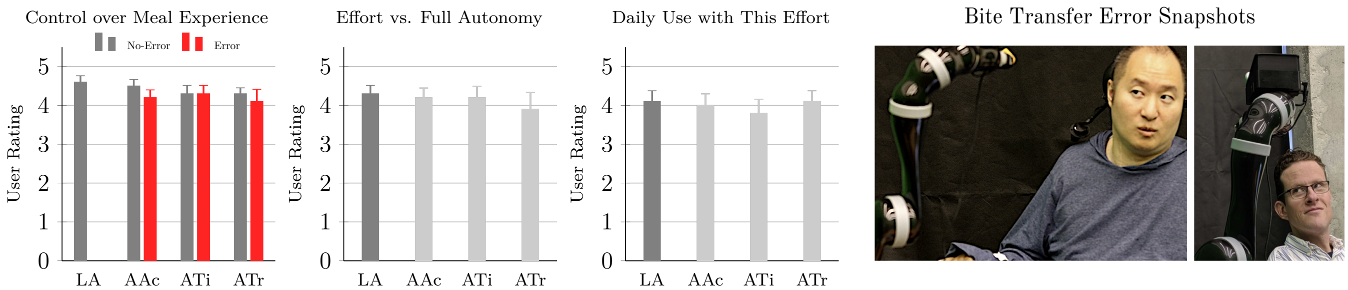

Figure 9: Effect of autonomy and its perceived error risks. Participants consider *low-autonomy* trials to require more effort compared to *fully autonomous* trials and partial autonomy does not help reduce the effort. Also, participants do not have a clear preference to use partially autonomous trials when compared with *low-autonomy* trials. Additionally, with autonomy comes potential risk of errors, and participants may have a negative preference for errors that *low-autonomy* trials may have higher perceived control over the meal experience compared to trials with erroneous partial autonomy. Generally, bite transfer errors may be penalized higher than other types of errors.

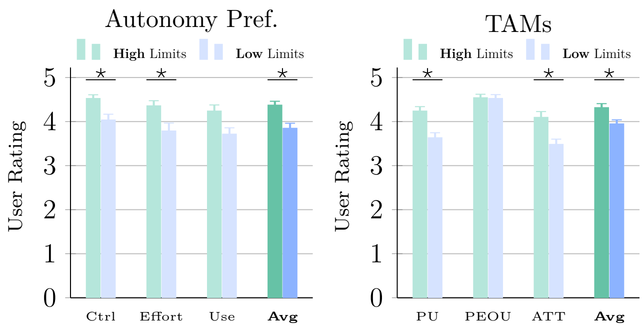

Figure 10: Findings on autonomy preference and TAM responses based on mobility grouping. Statistical significance was found for control, effort and the average over autonomy related questions; additionally, all TAM sub-groups were found significantly different except perceived ease of use (PEOU).

joints, or shaky hands that impede them from feeding themselves. Due to the online nature of the questionnaire, the videos were presented in the same order for all online participants.

We designed this study to have 7 trials total presented to the participants in four blocks with different modes of autonomy (See Section 3.2). The *low-autonomy* trial was considered a block by itself. One block had the *autonomous acquisition* trial followed by *autonomous acquisition with error*. Another block had the *autonomous transfer* trial followed by *autonomous transfer with error*. And the fourth block had the *autonomous timing* trial followed by *autonomous timing with error*. The four blocks were presented at a random order across the in person participants. The speed of the robot was fixed to the *fast* setting, the dining scenario was *individual* and the *web* interface was used for all trials. After each trial, the participants were asked questions about their preferences of autonomy and effort, their preference given errors and general technology acceptance questions based on the TAM model [26].

5.2 Findings

A General Linear Model was fitted for each dependent variable using *Mobility* and *Autonomy Level* as main factors. Interactions between factors was found non-significant and the following analysis focuses on the main effects.

More autonomy is not always better: Effect of errors. Fig. 9 shows the results. Even though the current experiment did not find any statistically significant differences between autonomy levels, there were trends. Participants usually preferred trials with no error compared to those with error when sufficient control over their meal experience or potential daily usage was considered. However, they *agree* that the *low-autonomy* trial requires more effort than the *fully autonomous* trials experienced earlier in Study 1 (See Section 4). Notably, partial autonomy does not help in reducing the effort. In terms of the *mobility* factor, as shown in Fig. 10, participants with higher mobility impairments gave significantly higher scores on items related to autonomy preference than participants with lower mobility impairments ($p < 0.03$). Interestingly, the participants still *agree* that they would use the robot with the increased effort with preference for the *low-autonomy* trial when compared to trials with partial autonomy. When asked about the percentage of errors during a meal that they would tolerate with increased autonomy, on an average they mentioned that they would be fine with bite-acquisition errors happening around 30% of the time but they penalized the bite-transfer errors slightly higher at a rate of 25%. Notably, none of the participants perceived the error in bite-timing in which the approach was delayed by 5s after detecting the mouth-opening. When responding to the post-task questionnaire, P1 mentioned that "I didn't like having it do step by step. I wanna say give me food and have it fly down there and give me food". P1 also made a remark regarding the lack of continuity of the feeding process from the robot side. P3 supported that statement with a similar one "Picking things up and selecting was slow (...) there was a lot of thinking going on"

Participants agree to the technology's perceived acceptance and usage. Similar to results from Study 1, mobility was found as a significant factor for TAM responses. As shown in Fig. 10, participants with higher mobility limitations gave significantly higher scores on perceived usefulness (PU), attitude (ATT), and on the average of all 10 TAM questions (Avg). The participants' preference for our robotic system in general is supported by the following statements gathered during the post task questionnaires: "There seem to be some limitations (...) it still wouldn't stop me from using it, let me be clear. Totally beats going hungry" (P2). "Overall great work, it was fun to use. None of the errors bothered me, especially when it didn't pick something up (...) I liked that it went ahead and it tried something new every time so that's great" (P4).

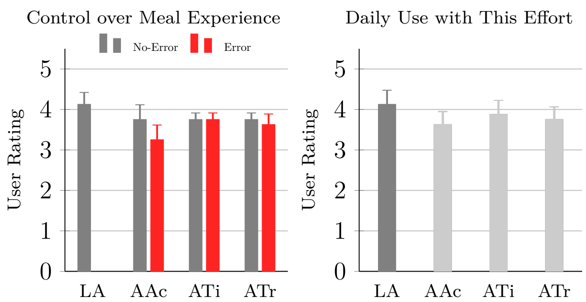

Figure 11: Results from online participants show preference to versions without error compared to with error. Also, participants agree that the *low-autonomy* version provides more control over the meal experience than the partial autonomy versions with error.

Table 2: Average TAM category responses for different modes of autonomy with and without error in the online experiments.

	Partial Auto			Partial Auto w/ Error			Low Auto
	AAc	ATi	ATr	AAc	ATi	ATr	
PU	**4.14** ±.19	**4.19** ±.16	**4.19** ±.18	4.00 ±.17	4.10 ±.18	4.00 ±.22	**4.14** ±.19
PEOU	3.81 ±.22	**4.00** ±.10	3.86 ±.16	3.38 ±.23	3.52 ±.15	3.71 ±.21	3.67 ±.21
ATT	3.93 ±.27	**4.14** ±.23	4.07 ±.25	3.93 ±.22	3.79 ±.19	4.00 ±.21	3.71 ±.32
ITU	3.57 ±.57	**4.14** ±.40	4.00 ±.44	3.43 ±.37	3.86 ±.46	3.57 ±.48	4.00 ±.49
PE	**4.14** ±.26	4.00 ±.00	3.57 ±.20	3.57 ±.20	3.71 ±.18	3.86 ±.34	3.29 ±.36

Online findings. Fig. 11 shows the results for the online responses. The current experiment did not find any statistically significant differences but the ratings show an overall decline when errors occurred. Also, similar to the in-person study, online participants usually preferred low-autonomy when compared to partial autonomy with errors especially for autonomous bite acquisition errors. However, note that the online participants experienced the trials from a 3rd-person viewpoint. Interestingly, among partial autonomy trials with no errors, *ATi* received the highest ratings. This could be because detecting the mouth opening is a clear sign of automation that is easily perceived even through video.

6 DISCUSSION

A video showing the experimental conditions is available in [17]. The studies with upper-mobility impaired participants show interesting insights about participants' preference about various factors that could affect human-robot interaction during the feeding task such as interfaces and speed in individual and social dining scenarios as well as autonomy given perceived error risks. However, note that even during the *low-autonomy* trials in the study when the human specifies the bite acquisition and bite transfer actions, the robot autonomously plans and executes these actions and thus, this mode has more autonomy than a fully teleoperated robot throughout the trial. It is extremely challenging to fully teleoperate a robot for assistive feeding due to the intricate manipulation actions involved in picking up these small bite-sized hard-to-model deformable food items. This is further confirmed by one of the statements that a participant made in Section 4.2, where he mentioned trying to teleoperate the robot to complete the same task as our study would take him around 45 minutes; the average time for the trials in our study was 1.5 minutes. From our post-task questionnaires with our in-person participants, we gathered some insight on the impact technology such as this can have on their lives: "Every little thing that I can do on my own is very important to me, and feeding isn't a little thing it's a huge thing and it's very important to me" (P1); "The main thing that would make this useful for me would be something that I could setup and run on my own, or I would need very minimal set up from somebody else. With the arm on my wheelchair that means it's always with me, that's half way there" (P4).

Note that we designed the experiment and tuned the system such that if given an option to skewer, it will succeed. For the trials with different modes of autonomy, we had trials with both successes and with errors that were deliberate. In real-life, it is completely possible that a non-autonomous robot commanded by a human can also have errors, but our assumption here is that humans are experts and if they choose an action, it should generally work. The possibility that humans may not be experts is not covered in this work. Also, note that we designed the controlled study such that the error recovery happens just after one try to make it consistent across participants and trials. In real-life the recovery may not be that fast, but in this study, we were interested in analyzing the effect of errors even with just one attempt for recovery. This was mentioned by P4 when he stated his preference on autonomy with a caveat "I think autonomous mode is better for most things unless there was an error. So one option could be if it did have a failure to, let's say pick up a food, then it prompts me how would you like me to proceed".

As engineers, these evaluations provide us with interesting guidelines for designing assistive robotic systems that are meant for daily use. Instead of focusing on designing a system that is fully autonomous, we can leverage human input whenever it is easily available without much effort to the user. Instead of spending many cycles on developing a technology that has flawless performance in the laboratory, we can design the system such that it achieves a desired performance with acceptable error risks for the target population and deploy it more quickly in the real world. Instead of designing a stiff system, we can provide multiple options of use such as different operation speeds, different modes of interaction because their usage is dependent on environment contexts that the target user is in. We hope to incorporate these insights into future iterations of our robot-assisted feeding system to more quickly and effectively provide greater independence to those in need.

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REFERENCES

[1] 2018. Meal Buddy. https://www.performancehealth.com/meal-buddy-system,[Online; Retrieved on 25th January, 2018].
[2] 2018. Meal-Mate. https://www.made2aid.co.uk/productprofile?productId=8&company=RBF%20Healthcare&product=Meal-Mate,[Online; Retrieved on 25th January, 2018].
[3] 2018. The Mealtime Partner Dining System. http://mealtimepartners.com/,[Online; Retrieved on 15th February, 2018].
[4] 2018. My Spoon. https://www.secom.co.jp/english/myspoon/food.html,[Online; Retrieved on 25th January, 2018].
[5] 2018. Obi. https://meetobi.com/,[Online; Retrieved on 25th January, 2018].
[6] 2018. ROVI Wheelchair. http://www.rovimobility.com/,[Online; Retrieved on 27th August, 2018].
[7] 2018. Winsford Feeder. https://www.youtube.com/watch?v=KZRFj1UZl-c,[Online; Retrieved on 15th February, 2018].
[8] 2019. Alexa Voice Service. https://developer.amazon.com/en-US/alexa/alexa-voice-service,[Online; Retrieved on 30th September, 2019].
[9] 2019. Beeson Automaddak Feeder. https://abledata.acl.gov/product/beeson-automaddak-feeder-model-h74501,[Online; Retrieved on 18th April, 2019].
[10] 2019. Bestic. https://www.camanio.com/us/products/bestic/,[Online; Retrieved on 18th April, 2019].
[11] 2019. Jamie. https://www.focalmeditech.nl/en/content/jamie,[Online; Retrieved on 18th April, 2019].
[12] 2019. Liftware handles. https://www.liftware.com/,[Online; Retrieved on 18th April, 2019].
[13] 2019. Neater Eater Robot. http://www.neater.co.uk/neater-eater-2-2/,[Online; Retrieved on 18th April, 2019].
[14] 2019. Nelson. https://www.focalmeditech.nl/en/content/nelson,[Online; Retrieved on 18th April, 2019].
[15] 2019. Tecla. https://gettecla.com/,[Online; Retrieved on 30th September, 2019].
[16] Redwan M Alqasemi, Edward J McCaffrey, Kevin D Edwards, and Rajiv V Dubey. 2005. Wheelchair-mounted robotic arms: Analysis, evaluation and development. In *Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics.* IEEE, 1164–1169.
[17] Robot assisted Feeding Video. 2020. https://www.youtube.com/watch?v=mLDyIWNGsy0&feature=emb_logo.
[18] Jenay M Beer, Arthur D Fisk, and Wendy A Rogers. 2014. Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of human-robot interaction* 3, 2 (2014), 74–99.
[19] Tapomayukh Bhattacharjee, Maria E Cabrera, Anat Caspi, Cakmak Maya, and Siddhartha S Srinivasa. 2019. A Community-Centered Design Framework for Robot-Assisted Feeding Systems. In *International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS).*
[20] Tapomayukh Bhattacharjee, Gilwoo Lee, Hanjun Song, and Siddhartha S Srinivasa. 2019. Towards Robotic Feeding: Role of Haptics in Fork-based Food Manipulation. *IEEE Robotics and Automation Letters* (2019).
[21] Zeungnam Bien, Myung-Jin Chung, Pyung-Hun Chang, Dong-Soo Kwon, Dae-Jin Kim, Jeong-Su Han, Jae-Hean Kim, Do-Hyung Kim, Hyung-Soon Park, Sang-Hoon Kang, et al. 2004. Integration of a rehabilitation robotic system (KARES II) with human-friendly man-machine interaction units. *Autonomous robots* 16, 2 (2004), 165–191.
[22] Steven W Brose, Douglas J Weber, Ben A Salatin, Garret G Grindle, Hongwu Wang, Juan J Vazquez, and Rory A Cooper. 2010. The role of assistive robotics in the lives of persons with disability. *American Journal of Physical Medicine & Rehabilitation* 89, 6 (2010), 509–521.
[23] Gerard Canal, Guillem Alenyà, and Carme Torras. 2016. Personalization framework for adaptive robotic feeding assistance. In *International Conference on Social Robotics.* Springer, 22–31.
[24] Alexandre Candeias, Travers Rhodes, Manuel Marques, Manuela Veloso, et al. 2018. Vision Augmented Robot Feeding. In *Proceedings of the European Conference on Computer Vision (ECCV).* 0–0.
[25] Young Sang Choi, Travis Deyle, Tiffany Chen, Jonathan D Glass, and Charles C Kemp. 2009. A list of household objects for robotic retrieval prioritized by people with ALS. In *2009 IEEE International Conference on Rehabilitation Robotics.* IEEE, 510–517.
[26] Fred D Davis, Richard P Bagozzi, and Paul R Warshaw. 1989. User acceptance of computer technology: a comparison of two theoretical models. *Management science* 35, 8 (1989), 982–1003.
[27] Treena Delormier, Katherine L. Frohlich, and Louise Potvin. 2009. Food and eating as social practice–understanding eating patterns as social phenomena and implications for public health. *Sociology of Health & Illness* 31, 2 (2009), 215–228.
[28] Håkan Eftring and Kerstin Boschian. 1999. Technical results from manus user trials. In *Proc. ICORR*, Vol. 99. 136–141.
[29] Nabil Ettehadi and Aman Behal. 2018. A learning from demonstration framework for implementation of a feeding task. *Encyclopedia with Semantic Computing and Robotic Intelligence* 2, 01 (2018), 1850001.
[30] M Evans. 1991. *Magpie: It's development and evaluation.* Technical Report. Technical report.
[31] D. Gallenberger, T. Bhattacharjee, Y. Kim, and S.S. Srinivasa. 2019. Transfer depends on Acquisition: Analyzing Manipulation Strategies for Robotic Feeding. ACM/IEEE International Conference on Human-Robot Interaction.
[32] Daniel Gallenberger, Tapomayukh Bhattacharjee, Youngsun Kim, and Siddhartha S Srinivasa. 2019. Transfer depends on Acquisition: Analyzing Manipulation Strategies for Robotic Feeding. In *ACM/IEEE International Conference on Human-Robot Interaction (HRI).*
[33] T M Gill, C S Williams, and M E Tinetti. 1995. Assessing Risk for the Onset of Functional Dependence among Older Adults: The Role of Physical Performance. *Journal of the American Geriatrics Society* 43, 6 (1995), 603–609.
[34] Kelsey P Hawkins, Chih-Hung King, Tiffany L Chen, and Charles C Kemp. 2012. Informing assistive robots with models of contact forces from able-bodied face wiping and shaving. In *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication.* IEEE, 251–258.
[35] Laura V Herlant. 2016. *Algorithms, Implementation, and Studies on Eating with a Shared Control Robot Arm.* Ph.D. Dissertation.
[36] Hiroki Higa, Kei Kurisu, and Hideyuki Uehara. 2014. A vision-based assistive robotic arm for people with severe disabilities. *Transactions on Machine Learning and Artificial Intelligence* 2, 4 (2014), 12–23.
[37] M Hillman and A Gammie. 1994. The Bath institute of medical engineering assistive robot. In *Proc. ICORR*, Vol. 94. 211–212.
[38] Kinova JACO. 2018. https://www.kinovarobotics.com/en/products/robotic-armseries.
[39] Alberto Jardón, Concepción A Monje, and Carlos Balaguer. 2012. Functional evaluation of ASIBOT: A new approach on portable robotic system for disabled people. *Applied Bionics and Biomechanics* 9, 1 (2012), 85–97.
[40] S. Javdani, H. Admoni, S. Pellegrinelli, S.S. Srinivasa, and J.A. Bagnell. 2018. Shared Autonomy via Hindsight Optimization for Teleoperation and Teaming. *The International Journal of Robotics Research* (2018).
[41] Dae-Jin Kim, Rebekah Hazlett-Knudsen, Heather Culver-Godfrey, Greta Rucks, Tara Cunningham, David Portee, John Bricout, Zhao Wang, and Aman Behal. 2011. How autonomy impacts performance and satisfaction: Results from a study with spinal cord injured subjects using an assistive robot. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 42, 1 (2011), 2–14.
[42] Vijay Kumar, Tariq Rahman, and Venkat Krovi. 1997. Assistive devices for people with motor disabilities. *Wiley Encyclopedia of Electrical and Electronics Engineering* (1997).
[43] I. F. Lin and H. S. Wu. 2011. Does informal care attenuate the cycle of ADL/IADL disability and depressive symptoms in late life. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 66, 5 (2011), 585âĂŞ594.
[44] P Lopes, R Lavoie, R Faldu, N Aquino, J Barron, M Kante, and B Magfory. 2012. Icraft-eye-controlled robotic feeding arm technology. *Tech. Rep.* (2012).
[45] Veronique Maheu, Philippe S Archambault, Julie Frappier, and François Routhier. 2011. Evaluation of the JACO robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities. In *Rehabilitation Robotics (ICORR), 2011 IEEE International Conference on.* IEEE, 1–5.
[46] David Marshall. 2005. Food as ritual, routine or convention. *Consumption Markets & Culture* 8, 1 (2005), 69–85.
[47] Isira Naotunna, Chamika Janith Perera, Chameera Sandaruwan, RARC Gopura, and Thilina Dulantha Lalitharatne. 2015. Meal assistance robots: A review on current status, challenges and future directions. In *2015 IEEE/SICE International Symposium on System Integration (SII).* IEEE, 211–216.
[48] Eiichi Ohara, Ken'ichi Yano, Satoshi Horihata, Takaaki Aoki, and Yutaka Nishimoto. 2009. Tremor suppression control of meal-assist robot with adaptive filter. In *2009 IEEE International Conference on Rehabilitation Robotics.* IEEE, 498–503.
[49] Yutaro Ohshima, Yuichi Kobayashi, Toru Kaneko, Atsushi Yamashita, and Hajime Asama. 2013. Meal support system with spoon using laser range finder and manipulator. In *2013 IEEE Workshop on Robot Vision (WORV).* IEEE, 82–87.
[50] Daehyung Park, You Keun Kim, Zackory M. Erickson, and Charles C. Kemp. 2016. Towards Assistive Feeding with a General-Purpose Mobile Manipulator. *CoRR* abs/1605.07996 (2016). arXiv:1605.07996 http://arxiv.org/abs/1605.07996
[51] Anupam Pathak, John A Redmond, Michael Allen, and Kelvin L Chou. 2014. A noninvasive handheld assistive device to accommodate essential tremor: a pilot study. *Movement Disorders* 29, 6 (2014), 838–842.
[52] Chamika Janith Perera, Thilina Dulantha Lalitharatne, and Kazuo Kiguchi. 2017. EEG-controlled meal assistance robot with camera-based automatic mouth position tracking and mouth open detection. In *2017 IEEE International Conference on Robotics and Automation (ICRA).* IEEE, 1760–1765.
[53] Chamika Janith Perera, Isira Naotunna, Chameera Sadaruwan, Ranathunga Arachchilage Ruwan Chandra Gopura, and Thilina Dulantha Lalitharatne. 2016. SSVEP based BMI for a meal assistance robot. In *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC).* IEEE, 002295–002300.
[54] Travers Rhodes and Manuela Veloso. 2018. Robot-driven Trajectory Improvement for Feeding Tasks. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* IEEE, 2991–2996.

[55] Sebastian Schröer, Ingo Killmann, Barbara Frank, Martin Völker, Lukas Fiederer, Tonio Ball, and Wolfram Burgard. 2015. An autonomous robotic assistant for drinking. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 6482–6487.

[56] ATI-IA Force-Torque Sensor. 2018. https://www.ati-ia.com/products/ft/ft_models.aspx?id=Nano25.

[57] Won-Kyung Song and Jongbae Kim. 2012. Novel assistive robot for self-feeding. In *Robotic Systems-Applications, Control and Programming*. IntechOpen.

[58] Kyle Strabala, Min Kyung Lee, Anca Dragan, Jodi Forlizzi, Siddhartha S Srinivasa, Maya Cakmak, and Vincenzo Micelli. 2013. Toward seamless human-robot handovers. *Journal of Human-Robot Interaction* 2, 1 (2013), 112–132.

[59] Yoshihiko Takahashi and Shinichiro Suzukawa. 2006. Easy human interface for severely handicapped persons and application for eating assist robot. In *2006 IEEE International Conference on Mechatronics*. IEEE, 225–229.

[60] Kanya Tanaka, Shenglin Mu, and Shota Nakashima. 2014. Meal-assistance robot using ultrasonic motor with eye interface. *International Journal of Automation Technology* 8, 2 (2014), 186–192.

[61] Noriyuki Tejima. 1996. Evaluation of rehabilitation robots for eating. In *Robot and Human Communication, 1996., 5th IEEE International Workshop on*. IEEE, 118–120.

[62] Mike Topping, Helmut Heck, Gunnar Bolmsjo, and David Weightman. 1998. The development of RAIL (robotic aid to independent living). In *Proceedings of the third TIDE Congress*.

[63] Michael J Topping and Jane K Smith. 1999. The development of handy 1. A robotic system to assist the severely disabled. *Technology and Disability* 10, 2 (1999), 95–105.

[64] Loek A Van der Heide, Bob Van Ninhuijs, Arjen Bergsma, Gert Jan Gelderblom, Dick J Van Der Pijl, and Luc P De Witte. 2014. An overview and categorization of dynamic arm supports for people with decreased arm function. *Prosthetics and orthotics international* 38, 4 (2014), 287–302.

[65] Maria Vila Abad, Gerard Canal Camprodon, and Guillem Alenyà Ribas. 2018. Towards safety in physically assistive robots: eating assistance. In *Proceedings of the 2018 IROS Workshop on Robots for Assisted Living*. 1–4.

[66] Margaret Visser. 2015. *The rituals of dinner: The origins, evolution, eccentricities, and meaning of table manners*. Open Road Media.

[67] Akira Yamazaki and Ryosuke Masuda. 2012. Autonomous foods handling by chopsticks for meal assistant robot. In *ROBOTIK 2012; 7th German Conference on Robotics*. VDE, 1–6.

[68] Akira Yamazaki and Ryosuke Masuda. 2012. Various foods handling movement of chopstick-equipped meal assistant robot and there evaluation. In *International Conference on Social Robotics*. Springer, 158–167.