

# Physically Assistive Robots: A Systematic Review of Mobile and Manipulator Robots That Physically Assist People with Disabilities

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Annu. Rev. Control Robot. Auton. Syst. 2024.  
7:123–47

First published as a Review in Advance on  
November 21, 2023

The *Annual Review of Control, Robotics, and  
Autonomous Systems* is online at  
[control.annualreviews.org](http://control.annualreviews.org)

<https://doi.org/10.1146/annurev-control-062823-024352>

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## Keywords

physically assistive robots, accessibility, user-centered design, human–robot interaction, assistive technology

## Abstract

More than 1 billion people in the world are estimated to experience significant disability. These disabilities can impact people’s ability to independently conduct activities of daily living, including ambulating, eating, dressing, taking care of personal hygiene, and more. Mobile and manipulator robots, which can move about human environments and physically interact with objects and people, have the potential to assist people with disabilities in activities of daily living. Although the vision of physically assistive robots has motivated research across subfields of robotics for decades, such robots have only recently become feasible in terms of capabilities, safety, and price. More and more research involves end-to-end robotic systems that interact with people with disabilities in real-world settings. In this article, we survey papers about physically assistive robots intended for people with disabilities from top conferences and journals in robotics, human–computer interactions, and accessible technology, to identify the general trends and research methodologies. We then dive into three specific research themes—interaction interfaces, levels of autonomy, and adaptation—and present frameworks for how these themes manifest across physically assistive robot research. We conclude with directions for future research.

**Activities of daily living (ADLs):**

“activities oriented toward taking care of one’s own body . . . they enable basic survival and well-being, such as bathing, toileting, dressing and eating” (2, p. 2)

**Mobile robot:**

a robot that can move its own base (e.g., a robotic vacuum cleaner)

**Manipulator robot:**

a robot that can manipulate objects—for instance, by picking them up and moving them around (e.g., a robotic arm)

**Physically assistive robot (PAR):**

a robot that provides assistance to humans through physical interaction

## 1. INTRODUCTION

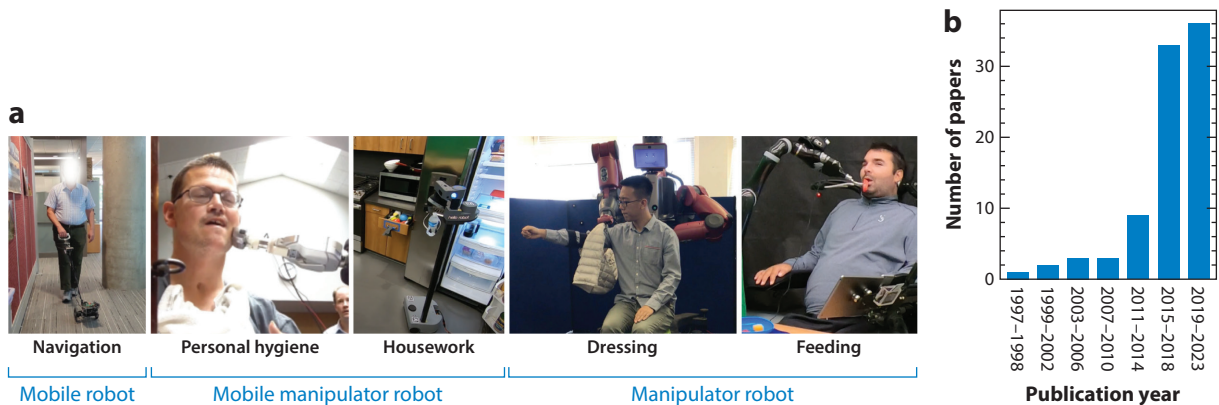
[Physically assistive robots] would decrease the workload on family members, help with caregiver burnout, and maybe in the future help a disabled person [like me] have more independence.

—Tyler Schrenk (<https://www.thetsf.org>), 1985–2023

The World Health Organization estimates that 1.3 billion people around the world experience significant disability (1). Whether due to congenital conditions, injury, illness, or age, disabilities can impact people’s ability to independently perform activities of daily living (ADLs; see Reference 2) and therefore reduce their quality of life. According to the US Centers for Disease Control and Prevention, at least 6 million adults in the United States have difficulty doing errands independently (3). While most people with disabilities wish to live independently in their home (4, 5), such difficulties can threaten their ability to do so. Besides their impact on day-to-day activities, disabilities also take a psychological toll and can lead to mental health challenges (6).

The social model of disability argues that disability is a result of the mismatch between a person’s abilities and their environment (7) and advocates to bridge the gap between our inaccessible world and diverse abilities. Universal design has helped bridge the gap in accessing the digital world, allowing people of many abilities to program computers and access the internet. However, the ability gap in accessing the physical world remains.

Mobile and manipulator robots present a unique opportunity for enabling access to the physical world for people with disabilities as they can sense the environment, navigate to different locations, and/or pick up and rearrange objects. Many ADLs that are difficult or impossible due to a person’s impairment—such as independently eating or ambulating—are physically possible for a robot to assist with or perform (**Figure 1a**). However, developing robots that safely and robustly perform these tasks in diverse environments, with diverse user impairments and preferences, is challenging. Many open questions remain as to how robots should be designed, what user interfaces to use, what levels of autonomy they should have, and more. These questions have fueled research in physically assistive robots (PARs) (see the sidebar titled What Are Physically Assistive Robots?).



**Figure 1**

(a) Common domains of assistance, exemplifying the different types of robots: mobile (8), mobile manipulator (9–11), and manipulator (12, 13). (b) Number of papers in this review by year published. Navigation image reproduced from Reference 8 (CC BY 4.0). Personal hygiene image reproduced with permission from Reference 10; copyright 2012 IEEE. Dressing image reproduced with permission from Reference 9; copyright 2019 IEEE.

## WHAT ARE PHYSICALLY ASSISTIVE ROBOTS?

Physically assistive robots (PARs) provide assistance to humans through physical interaction. PARs include robots that help users eat, dress, or move; pick up and move objects for users; replace limbs (e.g., prosthetics); rehabilitate limbs; augment the body (e.g., exoskeletons); and more.

This contrasts with socially assistive robots (SARs), which provide assistance to humans through social interactions. Examples of SARs and that are not PARs include robots that help provide autism therapy to children, serve as social companions to elderly people, and help motivate their users to exercise (14).

In this article, we survey papers about PARs intended for people with disabilities from top conferences and journals in robotics, human–computer interaction, and accessible technology. Three trends motivated this survey. First, over the past decade the number of papers researching PARs has increased severalfold (**Figure 1b**), yet PAR research has been siloed by domain of assistance (e.g., robot-assisted feeding and robot-assisted navigation), and there is little dialogue about take-aways that cut across these domains. Second, the formative studies (15, 16) that highlight the needs and preferences of people with disabilities tend to be published in venues focused more on human factors and do not always reach the roboticists capable of meeting those needs. Finally, PARs are increasingly being deployed in real-world settings (17–20), which is a welcome advancement but makes it more important to have conversations within the field about safety, robustness, working with people with disabilities, and more. Our goal with this survey is to fuel progress in PARs by (a) highlighting existing research, (b) inspiring more roboticists to apply their skills toward PARs, and (c) systematizing methods so that researchers can more easily work with people with disabilities.

## 2. RELATION TO OTHER SURVEY PAPERS

Newman et al. (21) presented a survey of physically and socially assistive robotics in general. Our work differs from theirs by focusing on people with disabilities, who have specific needs and constraints that must be taken into account when developing assistive robots.

Within survey papers focused on assistive robots for participants with disabilities, Matarić & Scassellati (14) focused on socially assistive robots (SARs), while two other survey papers (22, 23) focused on PARs. Although we report on themes similar to these covered in the latter two papers, those surveys were written before the last decade’s drastic increase in PAR papers (**Figure 1b**). Mohebbi (24) reviewed the human–robot interaction of PARs; while we have a section dedicated to interaction interfaces (Section 6.1), we also focus on other topics, such as the methods used in user studies.

Finally, some surveys have focused on assistive robots for particular populations—people with quadriplegia (25), older adults (26), and people with visual impairments (27). Our article brings together work focused on multiple types of disabilities and domains of assistance, to facilitate meaningful dialogue across the field of PARs. Finally, we note that there have been several recent surveys in prosthetics and rehabilitation robots (24, 28–32), which are beyond the mobile/manipulator robot scope of this survey.

## 3. SURVEY METHODOLOGY

We began by curating a list of top conferences and journals in robotics and assistive technology (**Figure 2**). From those venues, we searched for full papers whose title, abstract, or keywords had the term robot and at least one of the terms assistive, accessibility, disability, or impairment or

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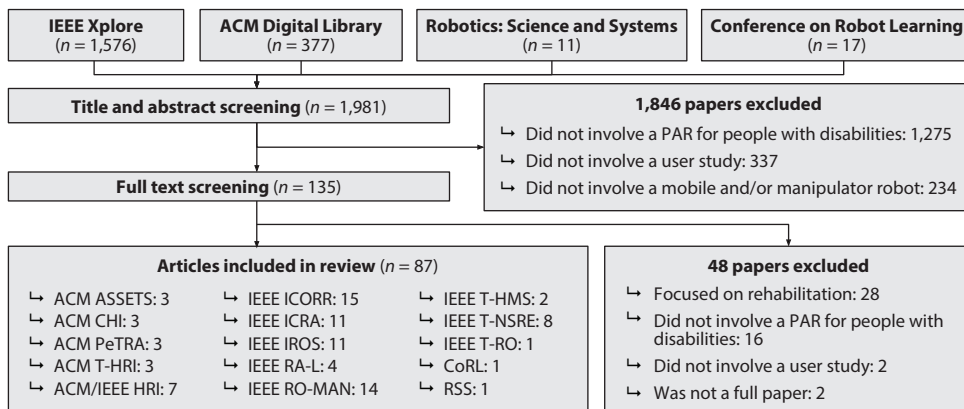
### Formative study:

a type of study that takes place in the early stages of system development and helps form the design for the system

### Interaction interface:

how users send information to and receive information from the robot, which includes the modality that is used for interaction (vision, audition, touch, etc.)

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**Figure 2**

The PRISMA flow diagram for this review. We screened 1,981 papers and included 87 in the article. Abbreviations: ACM, Association for Computing Machinery; ASSETS, ACM SIGACCESS Conference on Computers and Accessibility; CHI, Conference on Human Factors in Computing Systems; CoRL, Conference on Robot Learning; HRI, International Conference on Human-Robot Interaction; ICORR, International Conference on Rehabilitation Robotics; ICRA, International Conference on Robotics and Automation; IEEE, Institute of Electrical and Electronics Engineers; IROS, International Conference on Intelligent Robots and Systems; PAR, physically assistive robot; PeTRA, International Conference on Pervasive Technologies Related to Assistive Environments; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; RA-L, *Robotics and Automation Letters*; RO-MAN, International Conference on Robot and Human Interactive Communication; RSS, Robotics: Science and Systems; T-HMS, *Transactions on Human-Machine Systems*; T-HRI, *Transactions on Human-Robot Interaction*; T-NSRE, *Transactions on Neural Systems and Rehabilitation Engineering*; T-RO, *Transactions on Robotics*.

**Mobile manipulator robot:** a robot that can move its base and manipulate objects (e.g., a humanoid robot)

**Adaptation:** a process that changes the functionality, interface, or distinctiveness of a system to increase its relevance to an individual in a particular context

**Instrumental activities of daily living (IADLs):** “activities to support daily life within the home and community that often require more complex interactions than those used in ADLs” (2, p. 2)

other forms thereof. This resulted in 1,981 papers. We then screened the titles and abstracts to identify the papers that included (a) a PAR for people with disabilities or older adults, (b) a user study, and (c) a mobile, manipulator, or mobile manipulator robot.

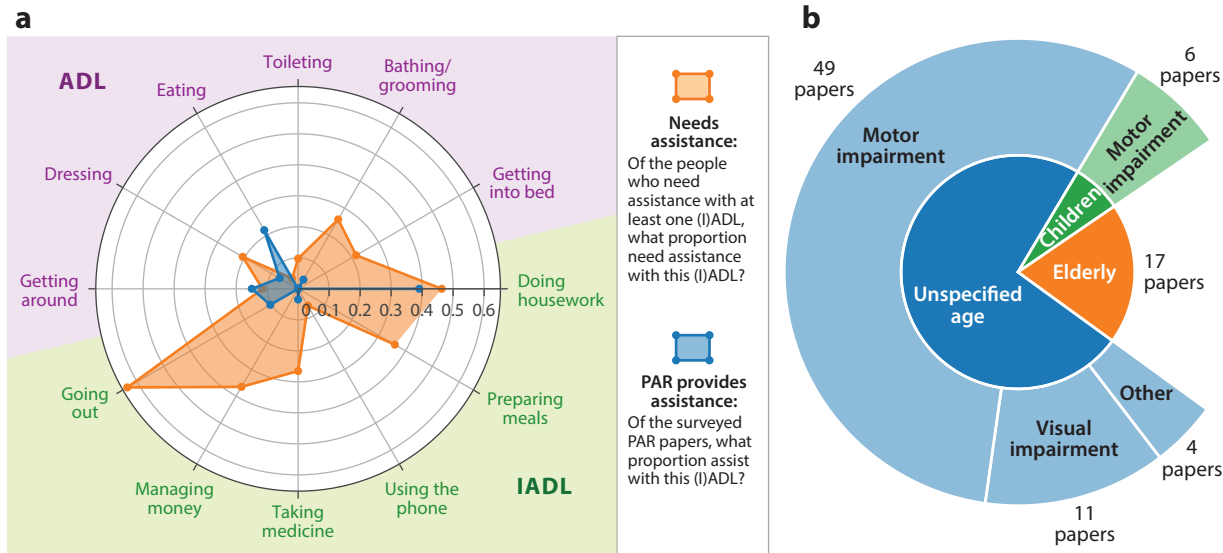
We aligned our interpretations of the above criteria by having a random selection of 60 papers tagged by two or three authors and discussing any differences until we reached consensus. The rest of the papers were split among the three authors for tagging. After this title and abstract screening, 135 papers remained. We then conducted full-text screening. At this stage, we also removed works that had a rehabilitation focus because of the existing surveys devoted to recent trends in rehabilitation robotics (24, 32), which resulted in the 87 papers included in this review. **Figure 2** shows the entire pipeline.

While reading the papers, we iteratively met to converge upon dimensions along which the papers were similar or different that would be of interest to the PAR research community. These dimensions were descriptive statistics (Section 4), types of user studies (Section 5), interaction interface (Section 6.1), levels of autonomy (Section 6.2), and adaptation (Section 6.3). For each dimension, we developed discrete codes by describing and clustering the works (bottom up) and then identifying existing frameworks that the codes mapped to (top down).

## 4. DESCRIPTIVE STATISTICS ABOUT THE PAPERS

### 4.1. Domain of Assistance

For every paper, we coded the domain(s) of assistance that the PAR helped the user with. This classification drew upon ADLs and instrumental activities of daily living (IADLs; see Reference 2), a framework for classifying the skills and activities necessary to live independently. We then



**Figure 3**

(a) The proportion of people who need assistance with each (I)ADL versus the proportion of PAR papers that assist with that (I)ADL. (b) Papers in this review by the target population's age (*inner circle*) and disability (*outer ring*). Abbreviations: ADL, activity of daily living; IADL, instrumental activity of daily living; PAR, physically assistive robot.

compared the proportion of PARs that focused on each (I)ADL with the proportion of people who need assistance with that (I)ADL (33) (see **Figure 3a**).

There are three spikes among PAR research, for (I)ADLs focused on navigation, feeding, and doing housework. For the navigation domain, we placed works that focused on navigating in any environment [e.g., fall prevention (34, 35) and standing assistance (36, 37)] under the category of getting around and works that focused on navigating in environments outside the home [e.g., guide robots for people who have visual impairments (8, 18, 38, 39)] under the category of going out. For the housework domain, we classified all pick-and-place works that focused on assisting with the general manipulation of objects as housework. However, such works can also help with going out (e.g., opening doors) and managing medication (e.g., bringing medication to a user). Note that even if the proportion of PAR research is similar to or greater than the proportion of people who need assistance, that does not mean our work is done; formative studies have found numerous ways in which all PARs must be improved (11, 40–43).

Some (I)ADLs—dressing, bathing/grooming, and managing medications—have a high user need for assistance but proportionately little PAR research. Extending the existing research in these realms (**Table 1**) would be a fruitful direction for future work. There are also some (I)ADLs that had no papers in this survey. Some, such as difficulty toileting and difficulty getting out of bed, may require special hardware (112, 113) that goes beyond the mobile/manipulator focus of this survey. Others, such as difficulty managing money or using the phone, are better served by nonrobotic solutions or SARs than by PARs (114, 115).

## 4.2. Target Population

We coded the target population age for each paper as children, elderly, or unspecified age (which was typically adults across ages). We also coded the target population's disability (if any) as motor

**Table 1 Domain of assistance and type of study for all papers in this review**

Domain of assistance	Formative		Summative: What is being evaluated?				
	Formative	Dataset	Interaction interface	Level of autonomy	Specific functionality	Whole system	
						In lab	In context
Getting around	—	44	36, 45	—	34, 35, 37, 44, 46–48	19, 49	19, 50, 51
Going out	18, 52	—	53	8, 38	53–55	18, 56	39
Eating	40–42, 57, 58	59	13, 42, 60	13, 61	59, 62–67	17, 68–70	17
Dressing	—	71	—	—	9, 65, 71–74	—	—
Bathing/grooming	—	10	—	—	75	68	10
Taking medicine	11, 76	—	11	—	—	77	76
Pick-and-place/ housework	11, 42, 43, 57	—	11, 78–89	12, 90–98	99–101	77, 78, 102–104	105, 106
Playing	107	—	107	—	—	108	109, 110
Working	—	—	—	—	—	—	111

impairment, visual impairment, or other.<sup>1</sup> **Figure 3b** presents the data. The bulk of PAR research is motivated by three target populations: people with motor impairments, people who are blind or low vision, and older adults. This drastically differs from the target populations of SAR research: people with autism, people with dementia, and older adults (14).

## 5. USER STUDIES ON PHYSICALLY ASSISTIVE ROBOTS

For every work, we coded the type of study, the number of participants with and without disabilities, what was being evaluated, and the methods used. We coded the type of study as formative, summative, or both. Formative studies take place in the early stages of research and help form the design for the system, while summative studies take place near the end of system development and help evaluate, or sum up, the system (15, 16). **Figure 4** and **Table 1** show the distribution of papers along these metrics. Of the 87 papers, 14 (16%) included a formative study, with the rest including only summative studies<sup>2</sup> (**Figure 4a**).

### 5.1. Involvement (or Lack Thereof) of Participants with Disabilities

Half of the papers involved no participants with disabilities, while the other half involved at least one<sup>3</sup> (**Figure 4a**). Notably, nearly all formative works involved people with disabilities. This is crucial to ensure that the early decisions that are made in a research area are informed by the needs of the target population. In contrast, the majority of summative evaluations involved only participants without disabilities. Some works framed these evaluations as preliminary, pilot, or proof of concept (53, 86, 87, 98, 103, 104), giving the impression that an evaluation with participants with disabilities is forthcoming. We found a few instances among the reviewed papers with a follow-up evaluation with participants with disabilities (e.g., Reference 11 followed up on

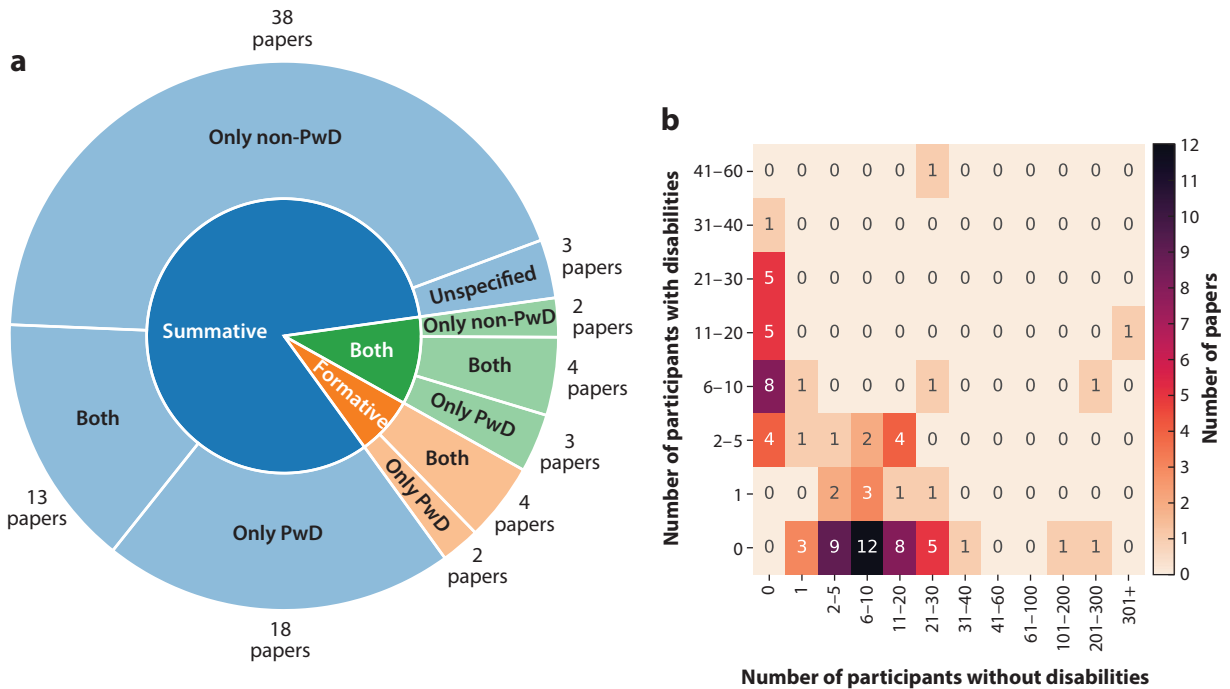
<sup>1</sup>Works with a target population coded as other either focused generally on people with disabilities (68, 111) or used a different form of categorization, e.g., people in skilled nursing facilities (72).

<sup>2</sup>All papers that collected data and trained a model were considered both formative (for the data collection and analysis) and summative (for the model evaluation).

<sup>3</sup>We determined whether people with disabilities were involved by reading the main text of the paper, which sometimes failed to mention whether a coauthor has the target disability. Some papers where members of the research team have the target disability include References 8, 18, 40, 52, and 54.

#### Summative study:

a type of study that takes place near the end of system development and helps one evaluate, or sum up, the system



**Figure 4**

(a) Papers included in this review by type of study (*inner circle*) and whether they included users with disabilities (*outer ring*). (b) Number of participants with and without disabilities each paper had. Abbreviation: PwD, people with disabilities.

Reference 88, and Reference 13 followed up on Reference 66). In other cases, researchers claimed to simulate disability among nondisabled participants through blindfolds (53, 55), braces (9, 72, 116), or intentional falls (e.g., to simulate older adults falling) (34, 35). Although simulations can provide a way to rapidly test the capabilities of a robotic system, they are considered problematic in the disability studies literature and should always be complemented with studies involving the target population (117).

Approximately a quarter of works involved participants with and without disabilities (**Figure 4b**). Some participants without disabilities were caregivers (41, 76), occupational therapists (41), or other stakeholders (18, 89, 106). In other cases, researchers ran a large-sample study with people without disabilities to collect statistical insights, followed by a small-sample study with people with disabilities to collect qualitative insights (11, 17, 19, 67, 100).

## 5.2. Formative Studies

Involvement of target users in formative research is particularly critical to ensure that researchers (a) work on problems that are actually important to the target users and (b) are aware of user constraints and preferences that should be taken into account when developing assistive technologies. This was reflected in the proportion of formative research in our survey that involved people with disabilities. On the other hand, the proportion of formative research to summative research was small, with only five papers that involved solely formative studies (40, 41, 43, 52, 57) and five that included a formative study and summative study (11, 18, 42, 76, 107). This is in contrast with other research focused on (nonrobotic) technology for people with disabilities. For example, a recent survey of technology for people with visual impairments found more formative than

summative research (118). One reason for this finding could be the lack of familiarity with formative research methods in the robotics community and the emphasis on quantitative findings.

Dataset collection for training a model was rare in the PAR literature, with only four papers (10, 44, 59, 71), despite the popularity of the approach in the robotics community. In all cases, the data were collected to model a component of the system, e.g., for gait tracking (44), force prediction (10), failure prediction (71), and bite timing prediction (59). None of the papers reported on generalizable formative insights based on the collected data.

A variety of formative research methods were exemplified in the papers: surveys (43, 57), interviews (18, 40, 57, 76, 105), group interviews (43, 57, 107), contextual inquiry (41, 57), participatory design (52, 57), observational studies (11, 42), workshops (57, 105), and ethnography (57). Some papers combined methods. For example, Beer et al. (43) conducted a written survey with older adults to assess the tasks they would like assistance with, and then followed up with a group interview to understand why they held those preferences.

Formative studies on PARs contribute insights that other researchers can use when designing, developing, and/or evaluating similar PARs. The findings from formative research can be presented as design constraints (76) or guidelines (40, 52, 119), evaluation frameworks (41), limitations of existing systems (11, 42), participants' concerns and potential opportunities (18, 58, 107), and directions for future work (40, 43). Note that some works conducted a formative study to understand the users' needs and then a summative study to evaluate the resultant system (18, 76), and some summative studies can also yield formative insights, such as users' preferences on the system's form factor (38).

### 5.3. Summative Studies

Summative studies either evaluate a specific component of the system (the middle three columns of **Table 1**) or the whole system (the last two columns of **Table 1**) and gather quantitative and/or qualitative data to conduct that evaluation.

**5.3.1. What is being evaluated?** Studies evaluating a system component focused on (a) the interaction interface (how users send and receive information to/from the robot), (b) the level of autonomy (how much of the sensing, planning, and acting of the system is done by the robot versus the user), and (c) specific functionality (any robot functionality that does not fall into the above two categories, such as domain-specific functionality). These studies typically compare the specific component of their system with one or more baselines, which are either state-of-the-art approaches (12, 36, 44, 59, 61, 79, 80, 82, 95, 98–100) or variants of their component with some subcomponents systematically removed, i.e., ablation studies (53, 55, 72, 74, 83, 93, 103, 107). Most of these studies are within-subjects, where each participant experiences every condition, which is better when there is high variance across participants (120), such as with participants with disabilities.

Studies that evaluate the whole system sometimes move beyond the lab and into the user's context of use. Of these, some are field studies, which involve running a structured study in the context of use (10, 50, 51, 109–111), while others are deployments, which involve letting users freely interact with the robot in the context of use (10, 17, 19, 39, 76, 105, 106). Note that most whole-system evaluations are noncomparative, possibly due to the large amount of resources required to develop a whole other system.

**5.3.2. What data are being collected?** Most summative studies in this review gathered quantitative data, which can further be divided into objective and subjective metrics. Objective metrics are often task specific, such as task completion time (11, 38, 82, 90, 95, 101), number of mode



switches (92, 96), success rate (45, 60, 99), and classification accuracy (59, 71, 75), among others. Subjective metrics often focus on user preferences regarding different versions of the robot. Many researchers create their own Likert-scale questions that focus on topics such as usability (51, 60, 61, 82, 90, 95), preference (38, 59, 90), satisfaction (17, 79, 92), feeling of control and safety (83, 100), and more. Others use standardized subjective metrics, such as the System Usability Scale (38, 77), the NASA Task Load Index (NASA-TLX) (8, 11, 19), and Psychosocial Impact of Assistive Devices (38). Note that objective and subjective metrics have complementary benefits—objective metrics are not impacted by biases in self-reporting, but subjective metrics are more grounded in users’ preferences (121)—resulting in many studies that use both (8, 11, 38, 60, 79, 90, 105).

Multiple summative studies paired quantitative data with qualitative data. Qualitative data can help to understand nuances of user preferences, gain insights into additional features users want, or contextualize quantitative results (122). To gather qualitative data, several summative studies held semistructured interviews (57, 76, 107) or focus groups (18, 39) after interacting with the robot, while others had participants share thoughts, insights, and reactions while interacting with the robot (11).

#### 5.4. Suggestions for Physically Assistive Robot User Studies

First, we caution PAR researchers to not overgeneralize from evaluations involving people without disabilities, as “there is not yet enough evidence supporting the generalization of findings from nondisabled subjects to the [target] population” (123, p. 9). Further, living with an impairment is very different from simulating one—“putting on a blindfold for half an hour . . . can’t give you the full experience of living with a visual impairment for . . . 40 years” (124, p. 9). While we acknowledge the challenges in running large-sample in-person studies with people with disabilities, alternatives exist (7), including remote studies (11, 13, 41, 100), video studies (40, 100), and working with a community researcher (40, 57).

Second, when using objective metrics (e.g., accuracy or efficiency), we call on PAR researchers to justify why those metrics align with user preferences. There is often the implicit assumption that users want their assistive robot to optimize the metric that researchers are measuring, but prior work has shown that this is not always the case (12, 13). As opposed to assuming an objective metric aligns with user preferences, it is important to work with users to identify objective metrics that align with their preferences.

Third, we recommend PAR researchers use standardized scales, such as the System Usability Scale (125) or NASA-TLX (126), for whole-system evaluations. Because most whole-system evaluations are noncomparative, it becomes difficult to compare research systems across different labs and papers. Standardized metrics can address this, since they are designed to work across a variety of technologies and have standard interpretations of their numeric scores (125, 127). In addition to the above standardized subjective metrics, standardized objective metrics that measure the user’s performance on a benchmark task can facilitate comparisons across works and create a universal interpretation of performance (e.g., the Action Research Arm Test used in Reference 128).

Fourth, we call for more formative research involving people with disabilities to inform the development of PARs. Formative research can be especially impactful if its findings are synthesized into open problems for robotics (e.g., 40), allowing other researchers to work on important challenges even without direct involvement by people with disabilities. Frameworks for describing assistance tasks and user requirements in detailed, structured ways, like SPARCS (Structuring Physically Assistive Robotics for Caregiving with Stakeholders-in-the-Loop) (129), can further increase the impact of formative work. Another avenue for accelerating progress based on formative research is the creation of robotics benchmarks and simulations for physical assistance. Choi et al. (130) created a list of household objects used by people with amyotrophic lateral sclerosis

(ALS), allowing researchers who work on pick-and-place tasks to focus on the objects most frequently needed by this user group. Ye et al. (131) conducted formative research with motor-limited individuals, caregivers, and healthcare professionals to inform the design of RCareWorld—a simulation environment with realistic human models representing different disabilities, home environments, and common assistance scenarios.

Finally, we call for more in-context research, particularly deployments. Unfortunately, there is a trend of relegating findings from in-context deployments of PARs to a small section within the paper (10, 17, 19). Although some may argue that small-sample deployments lack the statistical power of large-sample studies, we note that there is a large body of work in the experimental design and statistical analysis of *n*-of-1 studies that could add methodological rigor to PAR deployments (132).

## 6. OVERARCHING THEMES

### 6.1. Interaction Interface

One overarching theme across these works is the interaction interface that allows users to send and receive information from the robot. Some works explicitly focused on understanding the trade-offs between different interfaces for different individuals (79) or in different contexts (13, 40). Even works that did not explicitly focus on interaction interfaces still made design decisions as to which interface(s) best suited their application. This section provides an overview of the interfaces that are commonly used and trade-offs among them, based on the Senses and Sensors Taxonomy (133).

**6.1.1. Input interfaces.** The Senses and Sensors Taxonomy (133) differentiates between direct processing, or sensors that directly measure electrical stimuli sent from the brain, and indirect processing, or sensors that measure the outcome of those stimuli.

A small number of works use direct processing, such as electromyography (EMG) or electroencephalography (EEG), to convert the user's neural signals into inputs to the robot. Most works used EMG or EEG to teleoperate a robot in the pick-and-place domain of assistance (83, 102). Others combined EMG/EEG with another input device, such as muscle contraction (60, 80), brain signals (63), or eye gaze (93), to teleoperate the robot.

A larger set of papers involved indirect processing through modalities of vision, audition, touch, and kinesthetic inputs. The vision modality contains sensors that see user inputs and send them to the robot. One common application is detecting whether the user is ready for the robot to move toward their face in robot-assisted feeding (40, 70) or robot-assisted drinking (69). Another common application for vision is detecting an object that a user wants the robot to acquire, e.g., using a laser pointer (79) or a gaze tracker (70, 78, 87). Yet another application is to have the users completely control the robot with vision inputs (103).

The audition modality contains sensors that hear user inputs and send them to the robot. This modality includes interfaces that allow the user to give vocal commands to teleoperate a robot arm (82, 90). It also includes systems where the user uses voice to specify the object they want the robot to acquire, such as a specific bite of food (13). While audition sensors have the benefit of not requiring any body motion on the part of users, they may not work well in noisy settings (19) or social settings (13, 40).

The touch modality contains sensors that feel user inputs through direct contact and send them to the robot. This modality includes traditional methods of interacting with technologies, such as a mouse and keyboard (11, 77, 88, 91), joystick (17, 82, 89, 99, 108), or touchscreen (13, 52, 79). It also includes custom force-torque sensors used for robot-assisted navigation (38) or robot-assisted drinking (69).

The kinesthetic modality contains sensors that feel user motion and send that information to the robot. This modality includes using inertial measurement units to sense users' head

(60, 80, 85) and upper-body movements (81, 86) for teleoperation, or using rotary sensors (49) or pressure sensors (36) for teleoperation. Ranganeni et al. (8) used a force–torque sensor to detect when the user twisted the robot’s handle and turned the robot accordingly.

**6.1.2. Output interfaces.** Output interfaces are often used for the robot to communicate information to the user about its state, the state of the environment, or its feedback on how the user is completing the task. Relative to the number of PAR papers that incorporate input interfaces, comparatively few explicitly incorporate output interfaces. Papers that use the vision modality often display the robot’s camera feed to the user for teleoperation (11, 83, 102) or interaction (70, 91). Papers that use the audition modality use verbalization to greet the user (52, 77), provide feedback on what direction the user should move (38), or give the user information on what the robot will be doing (13, 39, 53). Those that use the touch modality use haptic vibrations to convey to the user what direction the robot will move (8), the direction the user should move (45, 53), or the distance to obstacles (19). Those that use the kinesthetic modality adjust the position of a walker to help users restore their balance (34), adjust the force profile of a walker to help users stand up (37), or guide a user’s hand to their target (52, 78, 107). Note that some works also incorporate multimodality, such as using verbal instructions to tell users who are blind where to find the robot arm and then kinesthetically guiding their arm to the target (107).

**6.1.3. Future work on interaction interfaces.** The observations above about interaction interfaces in prior PAR research point toward several opportunities for further research.

First, there has been comparatively less focus on output interaction interfaces than input interaction interfaces. This is despite the fact that research has shown that users’ trust in robots, comfort around robots, and ability to help robots improve if the robot transparently communicates its current state and future intent to them (134–136). Therefore, we call on future research to investigate what output information users want to receive from their PARs and how that information improves the user experience. Note that robot motion is an implicit output interface that can expressively communicate the robot’s intent (135, 137) but was not investigated by any works in this survey.

Second, we note that some input interaction interfaces require additional devices (60, 78, 79, 83). However, past research has demonstrated that users want to limit the number of additional devices they have to work with in order to use an assistive technology (40). Therefore, we call for future research on how PARs can effectively integrate with assistive technology interfaces that users already use (sip-and-puff straws, button arrays, screen readers, etc.). PAR research that utilizes smartphones (13, 19, 39) or computers (88) as an interaction interface is one approach to this problem, as those devices already integrate with numerous assistive technologies.

Third, although some works focused on comparing interaction interfaces, they mostly evaluate preferences aggregated across all participants. Yet the reality is that preferred interaction interfaces can vary drastically across individuals and contexts of use (13, 40, 79). Further, users with different disabilities may need very different interfaces. Therefore, we call for future research to investigate in what ways users’ interface preferences vary with the individual and/or their context(s) and how we can provide a superset of interfaces—and a smooth experience of switching between them—to cover these various preferences and abilities.

## 6.2. Levels of Autonomy

Another overarching research theme is levels of autonomy. Autonomy is “the extent to which a robot can sense its environment, plan based on that environment, and act upon that environment with the intent of reaching some task-specific goal (either given to or created by the robot)”

(138, p. 77). This section provides an overview of levels of autonomy in PAR research, following the five guidelines in Beer et al.'s (138) framework for levels of autonomy in human–robot interaction.

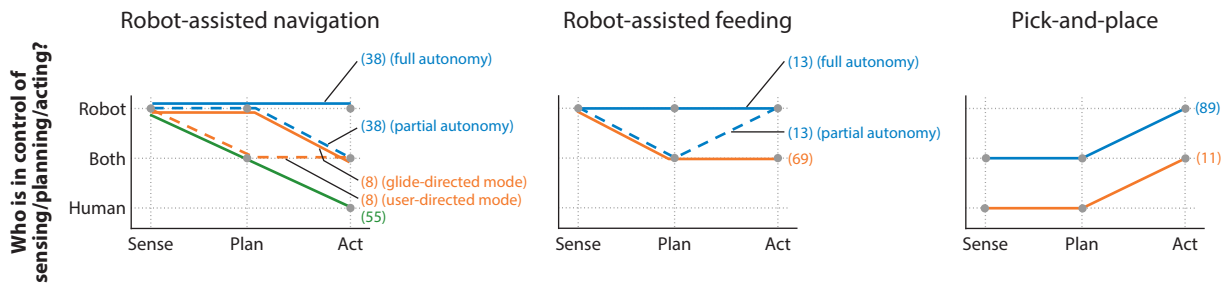
**6.2.1. Determining autonomy: What task is the robot to perform?** Beer et al. (138) stated that a key consideration for determining the level of autonomy of a robot is the impact of failures on its task. With PARs, the impact of failures is often high; a failure in robot-assisted feeding can result in choking or cuts, and a failure in robot-assisted navigation can result in collisions or falls. Therefore, there have been multiple efforts to enable robots to detect, predict, and/or avoid failures. In the case of robot-assisted feeding or shaving, this includes stopping as soon as an anomalous force is detected (10, 13, 67), as soon as the user winces or has other anomalous movements (67, 75), or as soon as an anomalous sound is detected (67). In the case of robot-assisted navigation, it includes predicting other pedestrians' motion and avoiding them (18, 39, 54) or predicting when users are becoming unbalanced and changing the robot's force profile to support them (34, 35, 37). There are also standardized methods for hazard analysis that have been applied to robot-assisted dressing (139).

Note, however, that automated ways of detecting and avoiding failure place accountability for system success on the robot, not the user, which users may not be comfortable with. Studies have revealed that users want full control to stop their PAR at any time, e.g., by pressing an accessible emergency stop button in robot-assisted feeding (40, 41) or by letting go of or ceasing to push the robot in robot-assisted navigation (8, 52). After stopping the robot, the user can teleoperate it and decide when it continues (140). In addition to giving users control to stop the robot at any time, another approach is giving users sole control to move the robot when near safety-critical areas—e.g., the robot moves toward the user's face only if they continuously face it or press on a force–torque sensor (69).

**6.2.2. Determining autonomy: What aspects of the task should the robot perform?** Beer et al. (138) divided tasks into three primitives: sensing, planning, and acting. Within PARs, which primitives the robot should perform is heavily influenced by the target population's impairments. PARs for people with visual impairments assist with sensing the environment to account for the user's reduced ability to independently do so (8, 38, 39, 52). PARs for elderly people who are sighted assist with acting, adjusting their force profile to account for the user's reduced ability to independently maintain balance (34, 35, 37). PARs for people with motor impairments also assist with acting, acquiring items and moving them to the user's face to account for their reduced ability to independently do so (10, 66, 69).

While the user's impairment can influence which aspects of the task they need assistance with, users also have preferences regarding which aspects of the task they want control over. Users often want control to set the robot's goal. For example, in robot-assisted feeding, users often want to select the bite the robot will feed them (40, 41), and in robot-assisted navigation, users often want to set the goal the robot is navigating them to (39, 52). In addition, users sometimes want control over how the robot achieves the task. Works in robot-assisted feeding have shown that some users want control over when the robot feeds them (13, 40, 41), and a work in robot-assisted navigation found that some users want control over which direction the robot turns at a junction (8). These works serve as important reminders that just because a PAR can do something autonomously does not mean that it should, a topic investigated by Bhattacharjee et al. (13).

**6.2.3. Determining autonomy: To what extent can the robot perform those aspects of the task?** Researchers can aim to automate as much of the assistive task as users are willing to have robots perform. However, achieving robust, generalizable robot autonomy in unstructured human environments is extremely challenging. What is possible to automate depends heavily on robot



**Figure 5**

Case studies of the levels of autonomy used in three different domains of assistance: robot-assisted navigation (8, 38, 55), robot-assisted feeding (13, 69), and pick-and-place (11, 89).

hardware (sensors, actuators, and compute) and the state-of-the-art algorithms of the day. When robust robot autonomy is not feasible, including the human in the loop [e.g., giving users control to stop the robot (38, 69)] can enable the robot to reliably complete its assistive task. Alternatively, one can modify the user's environment to make tasks easier to automate (141)—e.g., attaching towels to make drawers easier to manipulate (142) or attaching fiducials to make light switches easier to perceive (143).

Although the three questions for determining the level of autonomy restrict the levels that are available in a given situation, there might still be multiple options. It is advisable to make as many levels as possible available on a robot, as this can allow for customizing based on user preferences, having different interfaces for different users (care recipient versus caregiver), and context-dependent switching between levels of autonomy (e.g., falling back on lower levels when unexpected failures occur).

**6.2.4. Categorizing autonomy.** A variety of levels of autonomy are exemplified in the PAR literature (Figure 5). In robot-assisted navigation for people with visual impairments, although the robot has to be autonomous in sensing, there are a range of autonomy levels it can take on for planning and acting. Some robots autonomously plan and execute their route (38). Others autonomously plan but share execution with the user, e.g., having the user push while the robot steers (8, 38). Some yield part of the planning autonomy to users, letting them select the direction to turn (8). Yet others fully yield execution to the user—the robot suggests a direction, but the user is the sole agent pushing and steering the robot (55).

In robot-assisted feeding for people with motor impairments, some robots acquire the bite and move it to the user's mouth autonomously (13). Others let the user influence planning, by specifying high-level guidelines for how the robot should acquire the bite (13). Others let the user influence acting, by controlling how much the robot tilts a drinking glass (69).

In pick-and-place for people with motor impairments, some works had the user teleoperate the robot, by doing the sensing, carrying out the planning, and controlling its base and arm motion (11). Others had the robot and user sense the environment, had the robot present discrete grasping strategies to the user, and then had the robot autonomously grasp the item (89).

As indicated by this range in levels of autonomy for PARs, there is not one level of autonomy that is strictly better than others. Multiple works have found that user preferences for level of autonomy vary based on environmental- and individual-level factors (8, 13, 38).

**6.2.5. Influence of autonomy on human–robot interaction.** The level of autonomy of a PAR affects users' feelings of comfort, trust, and safety. Some works found that users feel more

comfortable when they have more control over their PAR (8, 38). Others found that users have safety concerns regarding interacting with a fully autonomous robot (13, 40). Another work found that users lose trust in a PAR that fails while operating autonomously, such as colliding with an obstacle (8). Yet another work found that not only the level of autonomy but also the level of transparency influences users' experience of the robot (91).

**6.2.6. Future work on levels of autonomy.** Despite the finding that users value a variety of levels of autonomy and will use them in different contexts (8, 13, 38), most PAR papers focus on just one level. Further, despite the finding that the level of autonomy has an important impact on user experience (Section 6.2.5), most PAR papers do not justify why their level of autonomy is a good match for the task and target population. Therefore, we call for more PAR research that investigates the trade-offs across different levels of autonomy and provides guidelines on how to determine the most suitable level(s) of autonomy based on the PAR's domain of assistance, target population, and context(s) of use.

### 6.3. Adaptation

Another overarching research theme is adaptation (144, 145). We define adaptation as a process that changes the functionality, interface, or distinctiveness of a system to increase its relevance to an individual in a particular context (144). Note that this process is also referred to in the literature as personalization or customization; we opted to use the term adaptation as it is one of the recommended principles of ability-based design (145).

**6.3.1. The need for adaptation.** The need for adaptation is motivated by diversity in users' impairments, preferences, and contexts of use. Studies reveal that users want to customize their PAR's interaction interface, level of autonomy, and other specific functionality.

Regarding adaptation of interaction interfaces, one work found that users with greater mobility preferred a different interface for telling a robot to pick up an object than users with less mobility (79). Other works found that users' preferred interface for interacting with a robot-assisted feeding system depended on whether they were in a social context (13, 40).

Regarding adaptation of levels of autonomy, some studies found that users' desired level of autonomy when using a robotic navigational aide was both context dependent (e.g., is it a new environment or an unfamiliar one?) (8, 38) and individual dependent (8). Bhattacharjee et al. (13) found that users with higher mobility impairment preferred higher levels of autonomy than users with lower levels of impairment. Yet another work found that age could impact users' preferred level of autonomy when interacting with PARs (91).

Regarding adaptation of specific functionality, Chugo et al. (37) found that the support profile users desired from a robotic walker differed based on their level of motor impairment. Choi et al. (101) found that how a robot should deliver items varies based on the user's posture and body type. Azenkot et al. (52) found that users with visual impairments had different preferred speeds for robot-assisted navigation systems. Works in robot-assisted feeding have found that users' preferred bite size, bite timing, bite transfer motion, bite transfer speed, and more vary based on their impairment(s), preferences, and social context (40, 41).

**6.3.2. Adaptation in physically assistive robots.** We draw on the questions in Fan & Poole's (144) classification scheme to characterize adaptation in PARs.

**6.3.2.1. What is adapted?** There are several approaches to adapting interaction interfaces. Some studies found that, partly due to the large variance in ability levels for end users, the sensors used in input interfaces need to be calibrated per user (36, 70, 80, 81). Another study developed two interfaces: one for people with fine motor skills and one for people without (89). Yet another

study leveraged existing adaptation in the user's assistive technology ecosystem, by allowing them to use their own screen-reading applications to customize hearing speed (39). Note that companies such as Kinova (146) have for years provided the ability to interact with their device through a variety of interfaces.

Regarding adapting levels of autonomy, Zhang et al. (38) let users of a robotic navigational aide choose whether the robot operates in full or partial autonomy and found that users preferred less robot autonomy in environments that were less controlled (e.g., outdoor environments). These findings were mirrored by Ranganeni et al. (8).

Multiple works allowed users to adapt specific functionalities of the robot. One work enabled older adults to program custom skills on their robot, such as raising a tray when the microwave is on (77). Another work allowed users to customize a parameter that controlled how much the robot followed its own policy versus the user's inputs (97). Another study customized how close the robot brings an object to a user, based on the user's self-declared mobility level (100). Yet another work allowed the user to customize the robot's speed, speech, proximity to the user, and model of the user's movements (65).

**6.3.2.2. *Who does the adaptation?*** Works that allowed the user to adapt the robot focused on providing the user with knobs to tune the robot's functionality. In the case of the paper by Saunders et al. (77), those knobs consisted of an entire domain-specific language designed for customizing that PAR. In other cases, researchers designed multiple discrete modes and let the user select one (38, 89). In yet another case, researchers exposed a continuous parameter to the user and let them adjust it (97).

Works that used shared control to customize the robot typically had the user provide some data during a calibration phase and had the robot adapt its behavior based on that data. This included calibrating the sensitivity of sensors (36, 80), asking users for self-reported mobility level (100), and asking them to move through their full range of arm motion (9, 72).

Works where the robot adapted to the user had the robot observe or predict some attribute about the user and change its behavior accordingly. Erickson et al. (74) tracked the distance between the robot and the user's body in order to adjust the robot's motion to the user's contours. Ondras et al. (59) used information about when the user last took a bite and the gaze of other diners to predict when to feed the user.

**6.3.2.3. *When does the adaptation take place?*** A variety of works adapted the robot during its main execution. This includes works that allowed users to select one of multiple modes for robot behavior (38, 89), works where the user iteratively modified a parameter (97), and works where the robot tracked and adapted to attributes of the user (59, 74). On the other hand, all works that involved a calibration phase adapted the robot outside of main execution (9, 36, 70, 72, 80, 81, 86, 100). Further, works that involved the user preprogramming robot actions also involved adapting outside of main execution (77).

**6.3.3. *Future work on adaptation.*** Although the broader field of assistive technology has had considerable focus on adaptation, summarized by Wobbrock et al. (145), it has been a smaller focus of PAR research. This presents several exciting directions for future work.

First, certain application domains tend to focus on specific types of adaptation. For example, research into interface adaptation was largely in the domain of pick-and-place (36, 80, 89), although the need has also been established in robot-assisted feeding (40, 41). Similarly, research into adaptation to levels of autonomy was largely in the application domain of robotic navigational aides for people with visual impairments (8, 38), although the need has also been established in robot-assisted feeding (41) and pick-and-place (91). We call for more cross-domain

research in adaptation, particularly to investigate under what conditions insights on adaptation can be transferred across domains.

Second, although there are works across the “who does the adaptation?” spectrum, to the best of our knowledge there are no works that provide guidelines on how to decide who should do the adaptation for a particular robot, user, domain, or context. The same applies to guidelines regarding when the adaptation takes place. We call for research into user perspectives regarding who should do the adaptation, when it should be done, and how that varies across the application domain, user, and context.

## SUMMARY POINTS

1. Domains of assistance (Section 4.1): There have been three main foci in research on physically assistive robots (PARs): navigation, feeding, and general pick-and-place.
2. Involvement of participants with disabilities (Section 5.1): Nearly all formative works involved people with disabilities, while approximately half of summative evaluations involved solely participants without disabilities.
3. In-context deployments (Section 5.3.1): The few in-context deployments of PARs that have been done tend to be relegated to small sections within a paper, preventing the community from learning about and benefiting from the several research, engineering, and logistical decisions required to deploy a system.
4. Quantitative metrics (Section 5.3.2): Most summative evaluations gather task-specific objective data (e.g., completion time, number of mode switches, and success rate) and/or subjective data based on custom questionnaires measuring usability, satisfaction, feelings of safety, and so on.
5. Interaction interfaces (Section 6.1): PAR research covers a variety of input interfaces, from brain-computer interfaces to vision-based interfaces to touchscreens to kinesthetic interfaces. In contrast, comparatively less work has focused on output interfaces for the robot to communicate to the user.
6. Levels of autonomy (Section 6.2): Most PAR research uses a single level of autonomy, despite the fact that past work has revealed that users’ preferred level of autonomy varies with the individual and context.
7. Adaptation (Section 6.3): Several studies have found that users want their interactions with PARs to be customized to their impairment, their preferences, and their context. Although some works have investigated adaptation, those works are segmented across application domains, and few works have investigated trade-offs across who is doing the adaptation and when it takes place.

## FUTURE ISSUES

1. Domains of assistance (Section 4.1): We call on researchers to study underresearched activities of daily living (ADLs) and instrumental activities of daily living (IADLs) such as dressing, bathing/grooming, and managing medication. This research would also include conducting formative studies to ensure that the design and development of PARs in these domains are rooted in user needs (Section 5.2).



2. Involvement of participants with disabilities (Section 5.4): We call on researchers to include more participants with disabilities in their works. In addition to in-person studies, other ways to do so can include remote studies, video studies, or working with a community researcher.
3. In-context deployments (Section 5.4): We call on researchers to conduct and publish more in-context deployments. Experimental design theory for  $n$ -of-1 studies can be used to add methodological and statistical rigor to PAR deployments (132).
4. Quantitative metrics (Section 5.4): We call on researchers to use standardized quantitative metrics such as the System Usability Scale and the NASA Task Load Index (NASA-TLX) when evaluating systems, to facilitate comparisons across PAR research. We also call on researchers to work with users to ensure that objective metrics they gather align with users' desires for system functionality.
5. Interaction interfaces (Section 6.1.3): We call on researchers to investigate the desired output information users want to receive from their PARs, as well as how PARs' input and output interfaces can integrate with users' existing assistive technology ecosystem.
6. Levels of autonomy (Section 6.2.6): We call on researchers to be intentional about which level(s) of autonomy they use and justify why that is suitable for the task(s), user(s), and context(s). We further call for more research on the trade-offs between levels of autonomy, in order to derive guidelines for how to determine the most suitable level(s) of autonomy for a PAR.
7. Adaptation (Section 6.3.3): We call on researchers to investigate users' preferences regarding the different forms of adaptation—what is adapted, who does the adaptation, and when it takes place—and how that varies across domain of assistance, user, and context.
8. PARs in society: Developing PARs that are widely used requires engaging with government regulations (147), ethics (148), and factors that influence technology adoption (149). Therefore, we call for more research that places PARs within the context of the political, economic, and social systems that impact their usage.

## DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

## ACKNOWLEDGMENTS

This article is dedicated to the memory of Tyler Schrenk (<https://www.thetsf.org>), a dear collaborator, advocate, and friend. We thank Tapomayukh Bhattacharjee for his constructive feedback on the article. This work was partially funded by the Robert E. Dinning Career Development Professorship and National Science Foundation awards IIS-1924435 and DGE-1762114.

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