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A Quantitative Analysis of Activities of Daily Living: Insights into Improving Functional Independence with Assistive Robotics

Laura Petrich[1], Jun Jin[1], Masood Dehghan[1] and Martin Jagersand[1]

***Abstract*— Wheelchair-mounted robotic manipulators have the potential to help the elderly and individuals living with disabilities carry out their activities of daily living (ADLs) independently. Robotics researchers focus on assistive tasks from the perspective of various control schemes and motion types, whereas, health research focuses on clinical assessment and rehabilitation, arguably leaving important differences between the two domains. In particular, there have been many studies on which activities are relevant to functional independence, but little is known quantitatively about the frequencies of ADLs that are typically carried out in everyday life. Understanding what activities are frequently carried out during the day can help guide the development and prioritization of robotic technology for in-home assistive robotic deployment. Robotics and health care communities have differing terms and taxonomies for representing tasks and motions; we aim to ameliorate taxonomic differences by consolidating quantitative task data with prior results from subjective task priority surveys. This study targets lifelogging databases, where we compute (i) daily activity task frequency from long-term low sampling frequency video and Internet of Things sensor data, and (ii) short term arm and hand movement data from video data of domestic tasks. In this work, we aim to provide deeper insights and meaningful guidelines to focus research and future developments in the field of assistive robotic manipulation that support the needs and performance requirements of the target population.**

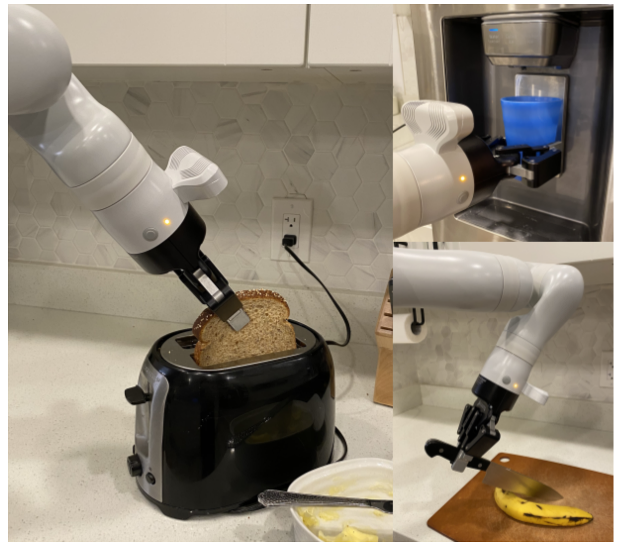

Fig. 1. Wheelchair-mounted robotic manipulators can help promote independent living by providing individuals living with upper-body disabilities with the means to carry out their activities of daily living on their own.

I. Introduction

Activities of daily living (ADLs) can be a challenge for individuals living with upper-body disabilities and assistive robotic arms have the potential to help increase functional independence [1]. Wheelchair-mounted robotic manipulators (WMRMs), such as the Kinova Jaco [2] and Manus/iArm [3], have been commercially available for over a decade. These devices can help to increase independence while decreasing the caregiver load and reducing healthcare costs [4]. WMRMs have the potential to be as important to individuals living with upper-body disabilities as power wheelchairs have become to those with lower body disabilities. However, outside of research purposes, only a few hundred assistive arms, primarily in Europe and North America, are practically deployed and in use. In this work we investigate what is impeding the successful acceptance and use of WMRMs in society. We present guidelines on where to focus future research and developments in the field of assistive robotic manipulation and motivate why it is important to understand and consider the needs of the target population (i.e., individuals that would benefit from having a WMRM available for use everyday) during the experimental design process.

[1]L. Petrich, J. Jin, M. Dehghan and M. Jagersand are with Department of Computing Science, University of Alberta, Canada

For the successful commercialization and acceptance of WMRMs in the general population it is imperative to understand what factors are related to assistive technology abandonment or disuse. In a survey study on device selection, acquisition, performance and use, four factors were found to be significantly related to device abandonment: lack of consideration of user opinion, ease of device procurement, poor device performance, and a change in user needs or priorities [5]. Chung *et al.* (2013) further claim that reliability, cost-efficiency, appearance, functionality, and usability are key factors necessary for the successful deployment of assistive robotic manipulators [6]. In this research, we focus on establishing an understanding of what functionality (i.e., task priorities) and usability (i.e., acceptable time limits for accomplishing a specific task) the target population requires of WMRM systems in order to decrease the risk of device abandonment and enhance user satisfaction.

The gap between robotic research and healthcare needs impedes the adoption of assistive devices. Healthcare professionals, assistive technology users, and researchers have differing biases as to which daily living tasks effort should be focused on. For assistive robotics research, knowing which ADLs are of high importance in the target population, as well as the necessary performance parameters for those high-priority tasks, will be crucial for real-world usability and

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deployment.

In order to build an task priority taxonomy with a focus on functional independence, it is important to first understand what defines independence and what is required to live independently; to this end we briefly review the World Health Organization Disability Assessment Schedule in section II [7], [8]. It should be noted that this classification was developed to determine an individuals level of disability and design appropriate rehabilitation plans, not to guide assistive robotics research.

Health care and robotic domains use different taxonomies to classify everyday activity tasks and motions [9], [10], [11], [12]. By merging these taxonomies and connecting health care needs with robotic capabilities we seek to bridge the two, often separate, communities. This would provide the robotics community with guidance as to which tasks have the potential to make a large impact (i.e., greatest increase in functional ability) on the target population if implemented. In the field of computer vision, recent interest in video object and activity recognition [13], [14] along with life-logging capture has resulted in numerous public data-sets [15]. In this work we aim to mitigate the gap dividing the health care and robotics communities; contributions include:

1) An analysis of long term video-recordings from publicly available life-logging data to extract quantitative measures of task priority;
2) From higher frame-rate video recordings of human kitchen activities, we analyze human arm and hand motion data to quantify the speed and variability of human movement; and
3) We discuss how understanding what tasks are of high importance, both quantitatively and qualitatively, will impact the acceptance and use of assistive robotic technology in the real-world.

Extracted task frequencies of everyday activities provide insight into what tasks would be of high priority for robotics researchers to focus efforts on while analyses of human motions during task execution provides a gold standard for robotic manipulation to compare against.

II. Functional Independence

Real-world acceptance and use of WMRMs depends on user satisfaction in the technology. To this end, we argue that understanding what functionality the target population requires of the system is crucial and that the first step towards this is knowing what defines functional independence. The International Classification of Functioning, Disability and Health (ICF) provides a framework for determining the overall health of individuals and populations [8]. Disability information is an important indicator of a population's health status, as it shows the impact that functional limitations have on independence. This concept is known as functional disability, or the limitations one may experience in performing independent living tasks [16]. Measures of functional ability involve assessing the potential capacity of a person to perform the tasks and activities normally expected to be carried out everyday; these are referred to as Activities of

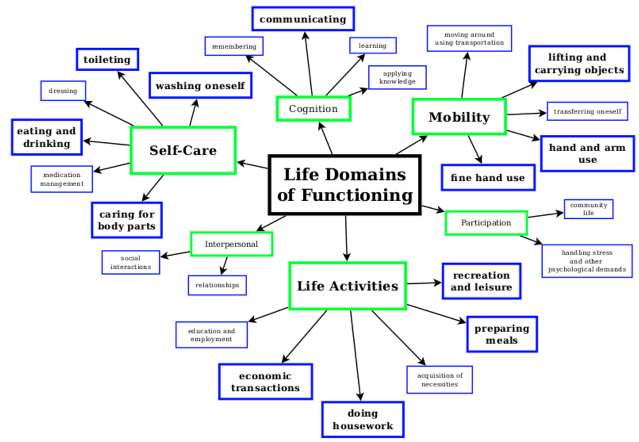

Fig. 2. The major life domains of functioning and disability as set out in WHODAS2.0; a standardized cross-cultural measurement of health status based on ICF. WHODAS2.0 is used to measure the impact of health conditions, monitor intervention effectiveness, and estimate the burden of physical and mental disorders across all major life domains. Physical motion activities relevant to robotics are highlighted in bold

Daily Living (ADLs) [9] and Instrumental Activities of Daily Living (IADLs) [10]. ADLs are basic self-care tasks essential for independent living. IADLs are more complex tasks that are still a necessary part of everyday life, but require a higher level of autonomy. Together they can be viewed as a high-level priority list of key life tasks to help guide the development of assistive robotic systems; in this work we will refer to these collectively as ADLs. The World Health Organization further developed the World Health Organization Disability Assessment Schedule (WHODAS2.0) from ICF as a standardized, cross-cultural measure of functioning and disability across all life domains [7], [17]. Figure 2 highlights these major life domains with associated tasks; the tasks most relevant to robotics research are emphasized in bold.

A common approach that drives research is to ask patients and caregivers for their preferences when it comes to robotic assistance [18], [19]. Notably, preferences vary and user opinions shift over time. In particular, a survey of 67 users surveyed both before and after they received and used an assistive robotic arm found that caregivers tend to favor essential tasks, such as taking medication. Pre-automation patients favor picking up dropped objects and leisure-related tasks, with a shift more towards work-related tasks post-automation [6]. In this work we combine user preferences with quantitative ADL data in order to provide guidance to the robotic community on which activities would make a meaningful impact in the target population.

III. Societal and Economic Impacts

The use of robotics to help increase functional independence in individuals living with upper limb disabilities has been studied since the 1960's. With improved system functionality, reliability, and ease of use, more individuals in need of help with their daily living tasks could be reached. The

Fig. 3. In the NCTIR Lifelog Dataset [22] 3 people wore lifelogging cameras for a total of 79 days. These are sample images of the subjects egocentric environment collected at a rate of 2 fpm.

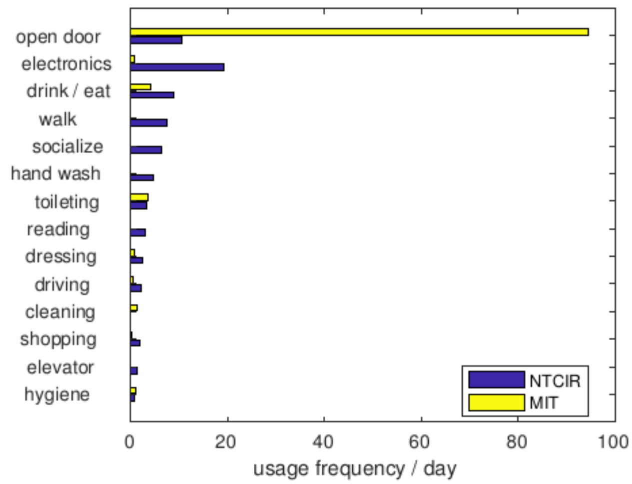

Fig. 4. ADL task frequencies captured from MIT IoT sensors (yellow bars) and NTCIR lifelogging video (blue bars).

United States Veterans Affairs estimate that approximately 150,000 Americans could benefit from currently commercially available wheelchair-mounted robot arms [6]. Many countries in the west and Asia have an aging populations, and disabilities can affect anyone, regardless of age. Canada has a multi-ethnic population and characteristics similar to other industrialized nations. The proportion of seniors (age 65+) in Canada is steadily increasing, with seniors comprising a projected 23.1% of the population by 2031 [20]. In 2014, seniors constituted only 14% of the population, but consumed 46% of provincial public health care dollars [21].

Power wheelchairs allow individuals with reduced lower-body function move around independently. As the reliability, functionality, and usability of WMRMs improves, they could help increase independence and reduce care needs for those living with reduced upper-limb function. Statistics Canada found from 2001 to 2006 there was a 20.5% increase in those identifying as having a disability, corresponding to over 2.4 million people in Canada [23]. One in twenty Canadians living with disabilities regularly receive assistance with at least one ADL on a daily basis, although not all of which will require the use of WMRMs. This suggests that there is a significant need for robotic solutions in Canada and similar countries world-wide. Some individuals may prefer automation integration with their smart homes, and some may require both cognitive and physical assistance. While artificial intelligence might provide some basic cognitive support, such as planning of the days tasks and reminders, it cannot eliminate the need for human contact and support. Robotic assistance can help free up humans from mundane chores, allowing more time for caregivers to focus on high-quality help and personal interaction.

With an increasing portion of the population requiring help with ADLs additional pressure is placed on government budgets and healthcare personnel. A four year study of WMRM users found that a robot reduced the nursing assistance needed from 3.7h/day to 2.8h/day [4]. While cost savings from reduced nursing care are significant ($20,000 USD/year), further savings and increased independence came from half of users being able to move out of assistive living and one quarter were able to rejoin the workforce. Furthermore, a key advantage of WMRMs is that they are with the person at all times.

IV. Activity Analysis from Lifelogging Data

Lifelogging data is a valuable source of quantitative ADL and human motion information. Lifelogging involves long-term recording of all activities performed by an individual throughout the course of a day, usually through a video camera, and occasionally using other types of sensors [15]. While lifelogging research has been published for over two decades [24], hardware and method innovation has made the field grow greatly within the past few years [25]. Small, wearable cameras, such as the Microsoft Lifecam [26], with a longer recording duration has made it more practical when compared with the analog video cameras and recorders used initially. New methods for recognizing objects and actions has driven Computer Vision (CV) research interests to explore lifelogging data, which has been found to be a source of more realistic "in-the-wild"-type data than typical CV benchmarks [27], [28].

In this work we evaluated over 30 lifelogging datasets, most of which targeted the performance of a particular algorithm (e.g., object recognition in home environments) and therefore did not encompass the full day. As a result, these datasets did not typically have a statistically sound sampling over all objects and tasks performed in a day in order to meet our analysis inclusion criteria for this work. We found that video recordings taken over several days were done at 1-2 frames per minute (fpm), making the data useful for gross ADL task frequency and duration analyses, but unsuitable for capturing detailed timings of individual arm and hand motions. An additional downfall of the low frame rate video datasets is that they fail to capture daily tasks repeated with high frequency but performed quickly, such as opening doors or turning on lights. A higher frame rate (i.e., 30 frames per second) is required to capture detailed

Fig. 5. Sample images from the GTEA Gaze+ dataset showing the top 4 most frequent kitchen motion tasks.

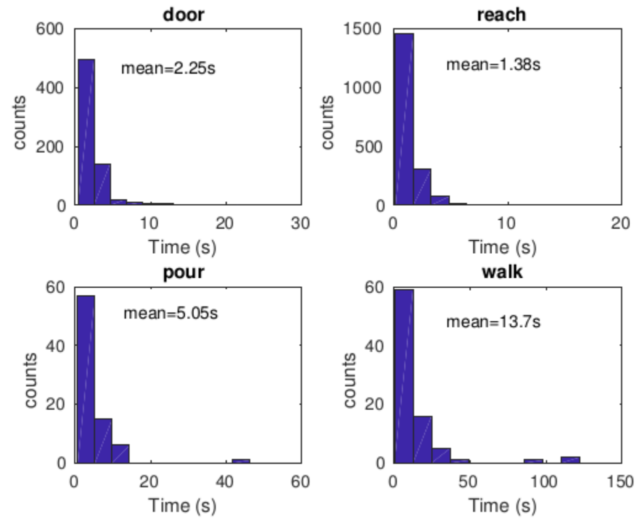

Fig. 6. Timing histograms for four common human motions. Human arm and hand motions are very quick and accurate, just seconds long. By contrast current robots are slow.

timings of individual arm and hand motions. In this work, three sources of data were selected for further analysis: two from long duration recordings to extract ADL task frequency and duration [15], [29], and one from short-term recordings of individual tasks for the motion data [30]. For a detailed table of all datasets considered for inclusion in this study please visit our companion website[1]

A. ADL Task Frequency Analysis

To compute quantitative data on ADL task frequency and duration we analyzed both egocentric lifelogging videos (referred to as 'NTCIR' [15], [22]), and exocentric data from Internet-of-Things (IoT) type sensing built into home objects (referred to as 'MIT') [29]. Example lifelogging images from the NTCIR dataset are shown in Fig. 3. Since the lifelogging video data was collected at only 1-2 fpm, the use of complementary sensing data turned out to be important for capturing a broader set of tasks. Tasks were inferred by manually labelling high-level actions in each image for a subset of the data and mapping them to automatically computed visual concepts provided with the NTCIR dataset. Our companion website[1] contains the visual context to actions inference bindings, so readers can replicate results or add other rules and actions to classify. This enabled us to label in-home data sequences spanning multiple days according to what ADLs were carried out at particular times and compute their statistics.

Figure 4 illustrates the frequency of the most common tasks found in these datasets, with the NTCIR video results shown in blue and MIT IoT sensor results in yellow. Tasks corresponding to potential robot skills are grouped together. Some events are detected more reliably by the embedded sensors used in MIT, others only in the lifelogging videos. For example, sensors detect quick events more reliably than the low frame rate lifelogging video data. In contrast, outdoor activities are only captured in the video data. By combining results from both datasets, we were able to obtain a more accurate quantitative measure of task significance.

It should be noted that this work is limited by the small sample size of people represented in the three datasets as well as the collection methods. The NTCIR Lifelog Dataset was collected over the course of a month for each of the 3 subjects with a camera worn on a lanyard around their neck passively taking images every 30 seconds. The MIT IoT dataset was collected over 14 days for 2 subjects with 77 state-change sensors installed in the first subject's apartment and 84 in the second subject's apartment. Given the small sample size we do not assume our results can be generalized across all populations, rather we aim to capture an ordering of task importance and magnitude of difference in frequency. A potential avenue for future work to help mitigate this limitation would be to capture full day video recordings of a diverse set of individuals at a higher frame rate.

Our results reflect that opening and closing doors is the most frequent task at 94 times per day; this category includes room doors, cabinet doors and drawers as they require similar robotic manipulation capabilities to carry out. We believe the MIT data was more accurate in this category since the data was obtained from built in door sensors, whereas the low video frequency of the NTCIR dataset missed quick openings, particularly of cabinet doors and drawers to retrieve objects. Using electronics is the second most frequent task performed; referring to the use of electronic handheld devices and was dominated by smart phone use. These devices were mostly not covered by the MIT sensors, but were detected in the NTCIR video data. Drinking and eating were found to be essential tasks in both studies, with a frequency of 8.8/day from NTCIR and 4.4/day from MIT. MIT captured hand washing every time the faucet was turned on or off, which

[1] http://webdocs.cs.ualberta.ca/~vis/ADL

resulted in an overestimation of hand washing frequency. We removed this outlier and relied on the NTCIR results of 4.7/day.

Task execution with a WMRM depends on the physical capabilities of the robot, as well as the time and cognitive load it takes the user to handle the human-robot interface. Door openings are covered in the literature [31], and robot feeding has been studied for over 30 years, with some prominent recent results [18], [32]. In contrast, hand washing, which is also high-priority, has been studied in assistive Computer Vision [33], to prompt Alzheimer patients though the steps, but, to the best of our knowledge, has yet to be studied in assistive robotic research.

These results capture the actions of able-bodied adults and can help guide robotics researchers as to what functionalities should be available in WMRM systems. A key finding in our work that was missed by subjective surveys on user preferences is that activities carried out on a frequent basis throughout the day should be easy and quick to carry out with a WMRM. We argue that activities that occur with high frequency but are not deemed as important by the target population should be carried out autonomously or semi-autonomously by the robot, as these tasks may not be worth the extra cognitive and physical effort required to manually control the robot during task execution.

B. Arm and Hand Motion Analysis.

The successful deployment and acceptance of assistive robotic manipulators also depends on the usability of the system. The goal of usability is to facilitate the user in accomplishing tasks within an acceptable time period; usability is influenced by the user interface and level of automation. In order to increase usability of WMRM systems, it is important to understand what an acceptable time period is for different tasks. Humans represent the gold standard for manipulation that WMRM systems should strive for and by analysing human arm and hand motion during task execution we can start to understand where potential frustrations during the control of WMRMs stem from.

From high frame rate video datasets we were able to extract the number and timings of individual arm and hand motions required to perform a particular ADL and, for a few tasks, similar timings for robot execution. The Georgia Tech Egocentric Activity Datasets (GTEA Gaze+) [2] contains full frame rate (30 fps) video recordings of humans performing domestic tasks [30]. We analyzed the annotated GTEA Gaze+ dataset, which contained 25GB of annotated kitchen activity videos to extract individual human motion timings performed during task execution (Fig. 5).

Figure 6 illustrates 4 common motions out of the 33 captured in the GTEA Gaze+ dataset. Notably, human motions were far faster than typical assistive robot motions. For example, reach motions that take us one second, can take anywhere from ten seconds to several minutes in published HRI solutions [34]. This has implications for how many tasks a robot system can practically substitute in a day without taking up an excessive amount of time. In other motions, such as pouring liquids, the task itself constrains the human to proceed slowly, thus there is not as much of a discrepancy between human and robot task execution times. The door task covers both lightweight cabinet doors and drawers, along with heavier doors (e.g. refrigerator); with lighter doors, the human times approached that of an unconstrained reach, despite the more challenging physical constraint of hinged or sliding motion, while heavier doors represent the long tail of the time distribution. It is important to consider that GTEA Gaze+ is not a representative sampling of all human activities that occur through the day as it was collected solely within a kitchen setting. However, it is still notable that the number of reaches captured in the dataset is 3x the number of door openings over the same 11 hours of video data. This implies that finding solutions for reliably and easily carrying out reaching motions with WMRMs would be beneficial for the target population in terms of reducing the cognitive load required and task execution time.

In Table I the frequency (occurrences per hour) and mean execution time for different kitchen motions captured in the GTEA Gaze+ dataset are presented. It is notable how quickly a human moves and how many movements we make while carrying out high-level activities (e.g., food preparation). Replicating human speed and agility is the gold standard to benchmark robots against.

Kitchen Motion Task	Frequency	Time (sec)
Reach and pick item	88	1.5
Reach and place item	84	1.2
Turn switch on or off	10	2.1
Wash hands or items	3	6.7
Flip food in pan	2	4.9
Transfer food	6	8.6

TABLE I. Frequency (occurences per hour) and mean execution time (seconds) for various kitchen tasks captured in the GTEA Gaze+ dataset.

V. Next Steps for Assistive Robotic Manipulation

Understanding which daily living tasks are of high priority to the target population as well as which tasks occur at a high frequency throughout the day can provide insight and guidance in the field of assistive robotic manipulation. Table II lists these high priority tasks; the qualitative column consolidates results from prior end-user surveys [18], [19], while the quantitative column highlights the key findings of this work. The quantitative results brings out common activities not mentioned in surveys, such as the frequent openings of cabinet doors and drawers, and the many switches and dials commonly found in homes.

Door opening/closing, drinking/eating, hand washing, and toileting would arguably be the most essential to support for assistive robot arm and hand systems, out of all the ADL tasks analyzed in this work. The first three are relatively feasible to accomplish given the payload capacity of current

[2]http://www.cbi.gatech.edu/fpv/

robotic arms. Activities, such as, using electronics (primarily smartphones), socializing, and reading could be physically aided by WMRMs, but since these activities are not inherently physical, alternative solutions are possible and can be a simpler and more reliable solution (e.g., hands-free phone use or other computational automation). Toileting is a high priority task that involves transferring from a wheelchair to the toilet. WMRMs do not generally support this, but there are specialized transfer devices that are used in health care, and can be easily installed in an individuals home.

Overall, there is great potential for supporting ADLs for those living with disabilities, as well as the elderly. Over the past few decades there has been an increasing demand for health care services due to the rising elderly and disability populations [35]. Assistive robots can help bridge this gap by alleviating the labor burden for health care specialists and caregivers. Furthermore, an assistive robot could help one perform ADLs they are otherwise incapable of managing on their own, thus increasing functional independence.

However, challenges remain before these robots will reach mainstream adoption, including but not limited to: system costs, task completion times, and ease of use via user interfaces. Currently costing around USD 30,000, an arm is a significant expense for an individual, who may already have a limited income. While western health insurance often covers expensive prostheses for amputees, only in the Netherlands does insurance cover a wheelchair mounted arm.

Speed of robot motion, which affects task completion time, is another challenge. While a human reach takes 1-2 seconds (Fig. 6), published assistive robots take 40-90 seconds, resulting in robot solutions that are magnitudes slower [36], [37], [34]. This results in decreased user satisfaction and promotes device abandonment. In the GTEA Gaze+ kitchen tasks, humans performed 160 reaches per hour. Substituting in reaching with a WMRM would turn a 30 minute meal preparation and eating time into a 2 hour ordeal. Anecdotal comments from users of assistive robot arms are that everyday morning kitchen and bathroom activities takes them several hours.

Robots tend to solve tasks differently than humans as robots are often limited to grasping one item at a time, while humans can handle many. For example, when setting a table, humans pick several utensils at the same time from the drawer, whereas a robot would move each utensil individually. Analysing the publicly available TUM Kitchen Data Set of activity sequences recorded in a kitchen environment [38], we found that their robot strategy on average required 1.6 times more movements than a human. Users of assistive robots adopt compromises to deal with the speed and accuracy of robots. For example, foods and drinks that can be held statically in front of the user by the robot (e.g., eating a snack bar or drinking with a straw) are far quicker to consume than those requiring numerous robot reach motions, such as eating a bowl of cereal.

It has been shown that users prefer to have continuous in-the-loop control, especially when the robot will be interacting directly with the individual, such as during eating [37], [36].

Qualitative	Quantitative
picking up items	reach to pick/place
carrying objects	opening/closing doors
preparing food/drinks	switches/buttons
eating/drinking	using electronics
personal hygiene	eating/drinking
leisure/recreation	hand washing
cleaning	toileting

TABLE II. High priority daily living activities that would have a large impact on the target community. The qualitative column reflects task priority preferences stated by the target population in surveys [18], [19]. The quantitative column highlights key results from our life-logging data analysis reflecting tasks that occur frequently throughout the day.

In recent work a low dimensional control space is learned from demonstrations. This allows a human user to have direct control over a 6 degrees of freedom motion using a low degrees of freedom human-robot interaction interface, such as a joystick [39], [40]. Getting the balance right between human interaction and semi-autonomous assistive systems will be challenging. Currently, most research is evaluated with a few participants trying it for about an hour each in a research lab setting. We expect that new human-robot interaction solutions will need to be deployed longer term in real users homes in order to properly evaluate functionality, usability, reliability and safety.

VI. Conclusion

In this paper we presented insights and meaningful guidelines that support the needs of the target population in order to focus research and future developments in the field of assistive robotic manipulation. Understanding what functionality (i.e., what tasks the target population expects to be able to carry out with an assistive robot arm) is critical for the acceptance and use of these systems in the real-world. We analyzed human task frequency from public life-logging datasets and computed motion timings from public Computer Vision data. A key finding of our quantitative analyses is that activities that occur at a high frequency but are not mentioned in user preference surveys would be ideal to be able to perform autonomously. Overall, reaching and door openings were the most frequently carried out motions. Drinking, eating, and hand washing are other high priority tasks that can be addressed by currently available assistive robot arms. Toileting and dressing, while ranking just below, are generally thought to be more challenging for robotics, since they require the transfer of body weight. Detailed data on frequency and duration information for all analyzed tasks and motions, as well as the analysis methods are available on our companion website: `http://webdocs.cs.ualberta.ca/~vis/ADL/`.

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