I Need a Third Arm! Eliciting Body-based Interactions with a Wearable Robotic Arm

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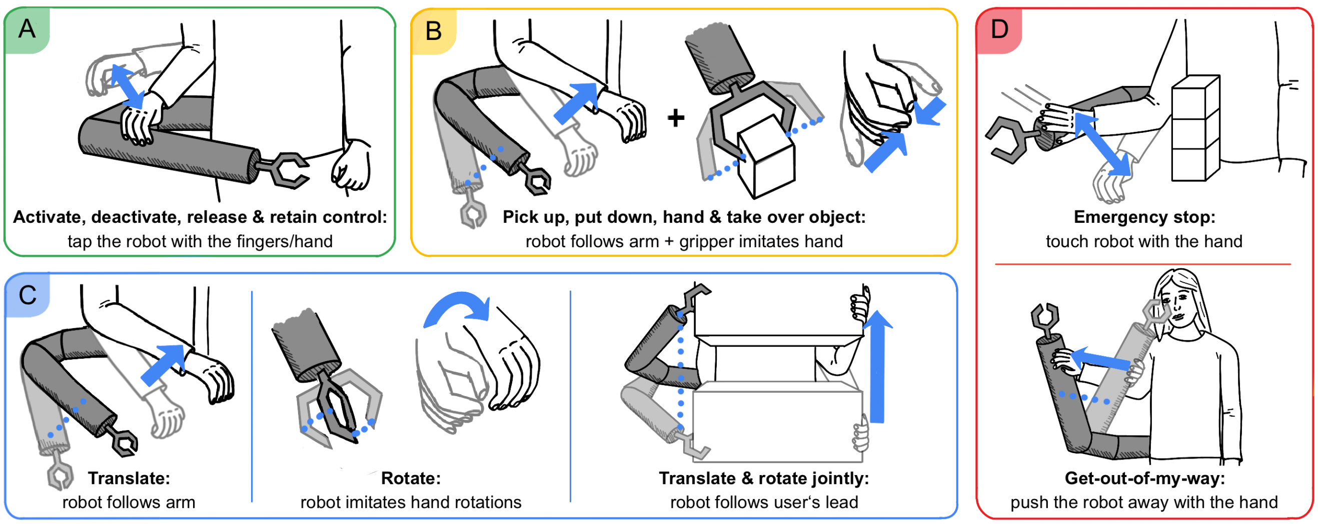

Figure 1: Several examples from the full set of 122 unique user-defined signs identified in this work. Touch-based gestures are particularly preferred for basic controls (A) or to handle emergencies (D), mid-air gestures for navigation (C) and object manipulation (B). A full listing of most preferred user-defined signs for hands-free and hands-busy settings is given in Table 2.

ABSTRACT

Wearable robotic arms (WRA) open up a unique interaction space that closely integrates the user's body with an embodied robotic collaborator. This space affords diverse interaction styles, including body movement, hand gestures, or gaze. Yet, it is so-far unexplored which commands are desirable from a user perspective. Contributing findings from an elicitation study (N=14), we provide a comprehensive set of interactions for basic robot control, navigation, object manipulation, and emergency situations, performed when hands are free or occupied. Our study provides insights into preferred body parts, input modalities, and the users' underlying sources of inspiration. Comparing interaction styles between WRAs and off-body robots, we highlight how WRAs enable a range of interactions specific for on-body robots and how users use WRAs both as tools and as collaborators. We conclude by providing guidance on the design of ad-hoc interaction with WRAs informed by user behavior.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Interaction devices**; **Gestural input**; • **Computer systems organization** → **Robotics**.

KEYWORDS

Wearable robotic arms; artificial limbs; supernumerary limbs; augmented arms; human-robot interaction; gesture; elicitation study.

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1 INTRODUCTION

Robots are moving onto the human body and hold great promise for assisting users in manual or physical tasks. Pioneering work has shown first examples of robotic limbs that can be worn on the user's body to provide a third arm [16, 56] or an additional finger [23]. The additional limb can either synergistically complement the basic function of human limbs, for instance a sixth finger can help to hold a large object; or it can act more independently, for instance holding a heavy item while the user is affixing it with a screw. Usage contexts range from professional, specific domains such as the reduction of workload of assembly workers [48], assisted crawling [13], or assisted learning of motor skills through robotic guidance [16, 35] to more personal applications in everyday life, such as carrying bags, moving hot items, or balancing large objects [71].

This very close integration of human and robot, and the resulting embodied partnership create new opportunities and challenges for human-robot interaction [22, 27]. While the Wearable robotic arm (WRA) may be able to perform some of its tasks autonomously, based on awareness of the task and context [58], we anticipate that many situations will require explicit user control and intervention. For instance, the user must be enabled to correct the robot's actions in real-time, to perform complex tasks through direct control of the robot, to flexibly manage collaboration without pre-planning task assignments, or to handle emergency situations.

However, these real-time interactions with a WRA have not been thoroughly investigated so far. Particularly, we lack a user-centric, systematic understanding of how users prefer to interact with a WRA. This is particularly critical since a WRA unifies characteristics of a body part, a hand-held tool, and an external collaborator. This opens up a unique interaction space, which is largely unexplored so far. A better understanding of this space is necessary for designing usable interactions with WRAs that people are actually willing to use in their day-to-day life.

In this paper, we contribute insights from the first elicitation study on human-robot interaction with a WRA. Based on user-elicited commands, we address the following key questions for the interaction with the robot, which impact usability and its design:

- What are principled ways that users would like to employ to interact with a WRA? What *body parts*, *input modalities*, and *input areas* do users prefer?
- What kinds of *signs* do users perform to control the WRA? How can interactions with WRAs be designed in a way that reflects user's preferences? Where do users draw inspiration from for the actions they suggest?
- Considering that a WRA can be particularly helpful in tasks where the user's natural hands are occupied with holding or manipulating objects, how do user's preferences change when *hands are occupied* in a primary task and therefore constraint or unavailable for human-robot interaction?

We conducted an unlimited gesture production elicitation study [14, 77] with a WRA form factor prototype to elicit gestures for a set of 14 robotic actions. These comprise, e.g., basic robot control, interaction with an object, interactions with a jointly held object, and handling situations of emergency. In addition, we also systematically investigated users' strategies used to control robot motion. We opted for using a passive physical prototype of a WRA that had the form factor of a third arm. It neither contained motors for actuation, nor any form of sensing or output. This allowed us to freely explore the design space in breadth and depth without restrictions imposed by limitations of today's technologies.

In this article, we present insights into preferred body parts, uncover what are preferred modalities of interaction, and present a detailed analysis of participant's preferred signs for all 14 actions, in hands-free and hands-occupied situations. These insights allow us to discuss implications for the design of interactions with WRAs and the required technology. With our work, we hope to get one step closer to the vision of natural and fluid interactions between robots and humans.

2 RELATED WORK

Our work is motivated by a lack of empirical studies for human-robot interaction, particularly regarding the design of and interaction with WRAs.

2.1 Human-Robot Interaction

With rapid advances in robotics and its application in many domains, we need a better understanding of human factors in human-robot interaction [61]. Particularly since humans seem to perceive robots to be neither a typical device nor a being, it is crucial to understand how to design interactions with such technologies [20, 28]. Of note, it is unclear how to best design interactions offering variable, but suitable levels of agency, which can range from teleoperation to fully autonomous agents [39, 63]. Some approaches suggest to assign tasks prior to the execution of a plan. But pre-planning of task assignments is problematic, as the human user might change their goals flexibly. Thus, it is especially crucial to understand how human-initiated, real-time control should be realized. For this purpose, elicitation studies have already been proven helpful in various areas [75, 77]. However, elicitation studies are rare for human-robot interaction. Some of the few examples elicit commands for a telepresence robot which should support communication between remote and local users [3], for a mobile robot [7], and most frequently for the control of single drones [8, 47, 59], and swarm drones [29, 51]. Our work addresses this knowledge gap through an elicitation study to understand how users desire to interact with a WRA.

2.2 Wearable Robotic Arms

Wearable robotics is a widely researched area [54]. Wearable robots cover various form factors, such as robotic legs [49], fingers [23], and arms [56, 72] which extend the human body, as well as medical prostheses [26, 31]. Whilst robotic prosthetic arms *replace* missing arms, we investigate robotic arms that *add* supernumerary limbs to augment the human body with additional functionality. Previous work has presented promising approaches to build such WRAs. The suggested designs show a broad variety, both for either single-arm [18, 50] and two-arm prototypes [16, 34, 56]. Common attachment points involve the shoulder to ease overhead work [5, 79], the forearm [71, 72], the upper arm [78], the hips [44, 73], or can be worn like a backpack [34, 56]. Whilst most WRAs have a rigid link-and-joint-based structure, enabling between 3 and 6 Degrees of Freedom [5, 56], there are also examples of soft robots that offer continuous deformations; for instance, Soft Poly-Limbs resemble a flexible elephant trunk which can manipulate objects through various end effectors [44, 45]. Similarly, Orochi is a soft WRA which can be worn like a scarf around the body [1]. Furthermore, there are also devices which are not exclusively third-arm systems, but their form factor allows them to be used as such since they consist, e.g., of a chain of servo motors [40].

Artificial intelligence allows to turn the WRA into an intelligent agent that can act autonomously, be task- and context-aware [58], or has the ability to adapt to behavioural patterns over time [66]. But research has also contributed a distinct set of mechanisms which allow for explicit human-initiated control. For instance, MetaArms control robotic arms through remapping feet motions directly on the robotic arms [56]. In addition, human hand positions [18, 45], shoulder motions [62], EMG sensors on the biceps [33], and vocals [72] have been suggested as a means to directly control the robotic arms. Brain-Computer Interfaces (BCI) have also been used for this purpose; for instance, Penaloza et al. used BCI to make a robotic arm grasp objects [50]. Beside body-centered interactions, we also find various examples which use external devices to control a robot. These involve, e.g., a joystick [44], a separate handle directly attached to the robotic arm [16], or a GUI which allows a user to program the robotic arm [1]. However, there are only few examples for which the suggested interaction techniques have been evaluated in terms of a user study with several participants [56, 71, 72]. Instead, the operability of the implemented system is commonly demonstrated through single-user proof-of-concepts. For instance, Guggenheim et al. demonstrated the usability of their system by showing how a person uses this system to open a door whilst hands are occupied with a primary task [18]. Consequently, research lacks systematic evaluations of the user's perception for the proposed interaction techniques. We address this gap with our empirical study.

3 METHOD

It is crucial to provide human operators with easy-to-use means for controlling robots, especially when they are novices or non-expert users. This need has been widely recognized and considered important in literature [11, 12, 18, 54]. Elicitation studies are a useful tool to empirically ground what interactions are found desirable by end users [32, 75, 77]. To the best of our knowledge, no previous work approached the interaction with WRAs from a user-centred perspective so far. We address this gap with this elicitation study using an unlimited production approach [14, 77]. We iteratively refined our study design through an extensive series of pilots. In the following we detail on the resulting prototype and procedure.

3.1 Prototype

As common in elicitation studies, we opted for a passive prototype, to avoid biasing the study results by restrictions of current technology, a specific set of sensors, or a certain type of output. The light-weight prototype has the form factor of a WRA, made of soft but stiff PE foam tubes and a plastic gripper (see Figure 2).

Figure 2: Study setup with the WRA form factor prototype. The backpack-worn arm is made of foam tubes, a basic gripper, and one articulated joint. The experimenter uses a stick to control it.

Hereby, we took inspiration from existing designs of robotic arms. Particularly, we opted for a rigid link-based structure. For simplicity, we decided to only model one articulated joint. The robotic arm's dimensions are based on the average length of a female extended arm (73.4 cm) [53]. The prototype can be worn like a backpack, as frequently proposed in the robotics community [16, 35, 57]. The robotic arm can be moved by the experimenter through an extension stick attached to the arm, but can also be freely moved around by the user. The extension stick was chosen to ensure the experimenter did not invade participants' personal space when moving the prototype. Furthermore, the prototype can be worn either left or right such that it can be attached at side of the user's dominant arm. In initial pilot studies, we had alternatively tested using human arms covered with textile to simulate the robotic arm in Wizard-of-Oz style, similar as suggested by [69]. However, we found that human arms were prone to bias as some participants felt uncomfortable with the experimenter standing closely behind them and hesitated to touch the human arm for interaction.

3.2 Procedure

Our study procedure is modeled after comparable gesture elicitation study designs in HCI, e.g., [75, 77]. We adapted the elicitation procedure through increased production to enable a broader exploration of signs and to reduce legacy bias [14]. The study session took place in a quiet environment, in single-user sessions. Participants suggested signs while standing in front of a table. After collecting informed consent and demographic information, we asked the participant to put on the WRA. Our main study procedure followed three steps, done for each referent:

First, we presented the participant with one of the 14 referents (see Table 1), each introduced by reading out their textual description. The order was fixed such that the referents' complexity and the presented level of robotic autonomy was increasing. Refer to Appendix A for the concrete instructions read out. We further demonstrated the effect of the referent by acting out motions using

Group	Referent	Referent Description
Basic Control	Activate	The user activates the robot. It goes from standby into listening mode.
	Deactivate	The user deactivates the robot. It returns to standby.
	Release Control	The robot goes into autonomous mode.
	Retain Control	The robot returns from autonomous into listening mode.
Robot Motion	Translate	The robot moves left, right, up, down, forward, backward.
	Rotate	The robotic gripper rotates left, right, up, down, clockwise, counter-clockwise.
	Translate Object Jointly	The user and the robot move a jointly held object to a specific location.
	Rotate Object Jointly	The user and the robot rotate a jointly held object by a specific angle.
Object Manipulation	Pick Up Object	The robot picks up an object.
	Put Back Object	The robot puts an object down on the table.
	Take Over Object	The user takes over an object from the robot.
	Hand Over Object	The robot takes over an object from the user.
Handling Emergencies	Emergency Stop	The user intervenes the robot's action. It stops immediately.
	Get-out-of-my-way	The robot moves out of the user's view.

Table 1: The list of 14 referents, their descriptions, and assigned groups. The list reflects a range of referents for basic control, to navigate the robot, manipulate objects, and handle unexpected emergency situations.

the WRA to create a more realistic interaction. As our pilot studies had indicated that user suggestions were biased by functionalities offered by specific objects such as screwdrivers or other tools, we opted against using such objects, and instead used generic styrofoam cubes ($10 \times 10 \times 10$ *cm*). Similar approaches using a 2D- or 3D cube world have been proven useful in prior studies [36, 77].

Second, after demonstrating the effect of a referent, we asked the participants to suggest signs which they would prefer to use for this command, without accounting for any potential technological constraints. Aiming for a focused analysis, we restricted suggestions to non-verbal signs. To reduce legacy bias, participants could suggest as many signs as they wanted [14]. We encouraged them to think aloud to obtain rich qualitative data that would be indicative of their mental models. We specifically asked them to verbally describe the signs they performed and to describe their reasoning as accurately as possible.

Third, given their set of non-verbal signs for a referent, we then asked participants which of their suggestions was their overall favorite and why. In case the suggested sign was not compatible with a hands-occupied setting, i.e., when the preference involved motions with the hands or arms, we asked for an alternative preferred sign that can be used in hands-occupied. As for four of our referents, one hand is naturally part of the interaction because the referents themself involve, for instance, that the hand is holding an object jointly with the robot, participants were allowed to select signs involving the corresponding hand for the hands-occupied setting, but not the other hand. This procedure allowed us to collect a variety of signs per referent and understand user preferences and patterns both under hands-free and hands-occupied conditions.

The elicitation was complemented through interleaved questions which asked, for instance, about challenges that participants see for the interaction with the robotic arm when controlling its motion or when the arm acts autonomously. Each session took around 90 minutes and was video-recorded.

3.3 Referents

We elicited signs for 14 referents, listed in Table 1. We opted for domain-independent commands that cover different types of interactions with a robot which serves to enable a broad exploration. The set of commands was evolved iteratively through consultation with literature, a series of pilot studies, and discussions amongst co-authors. We grouped the commands into four main categories: *basic control*, *robot motion*, *object manipulation*, and *handling emergencies*. We selected ACTIVATE and DEACTIVATE as referents for basic control of the robot's functionality. As robots can offer autonomous actions that the user might need to trigger explicitly, e.g., as mentioned in [58], we included two referents in which the user delegates control to the robot to complete a task autonomously (RELEASE CONTROL) and retains control afterward (RETAIN CONTROL). To allow for interleaved phases of direct human control in mixed-initiative settings, we further included two navigation and object manipulation referents, respectively, that give the user more explicit control and allow for low-level intent communication: TRANSLATE, ROTATE and PICK UP, PUT DOWN. These basic navigation and manipulation tasks have been frequently addressed in prior work, e.g., [16, 18, 44, 56, 72]. As robotic arms are also promising for jointly moving objects together with the user or for handover tasks [2, 71, 72], we complemented the existing navigation and manipulation referents by their collaborative counterparts TRANSLATE JOINTLY, ROTATE JOINTLY and HAND OVER OBJECT, TAKE OVER OBJECT. Lastly, due to the WRA's proximity to the human body, handling emergencies is particularly crucial to avoid endangering the user or invading their personal space. To better understand how the user wants to intervene in such undesirable actions, we included EMERGENCY STOP where the user "aborts" [7] or "stops" [74] the robot, and GET-OUT-OF-MY-WAY which tells the robot "Don't get too close to me" or "Go away" [17].

3.4 Participants

We recruited 14 voluntary participants (7 female, 7 male, 0 diverse; M = 23.5 y; SD = 7.0 y; 13 right-handed, 1 left-handed) for the study. They received a compensation of 15 Euros. Participants had various cultural backgrounds (Europe, Middle East, Far East, Central America). Their occupations included pupil, secretary, pharmacist, researcher, and students in law, education, cultural sciences, pharmacy, computer linguistics, data science and artificial intelligence. One participant was experienced in interaction design and implementation of off-body robotic arms.

3.5 Data Analysis

We analyzed the video recordings inductively and iteratively. To this end, we first transcribed participants' verbatim statements and all signs and variations through textual descriptions of the exact sign they demonstrated. This resulted in a total amount of 635 signs. Each participant suggested an average of 3.2 signs per referent (SD = 0.8), and a total between 30 and 75 gestures (M = 45.4, SD = 11.9). After merging identical or similar suggestions (e.g., pointing with the index finger and with the full hand were considered similar), we ended up with 197 unique signs. We then filtered for signs that were suggested by more than one participant or were a participant's favorite. This *consensus threshold* of two as introduced by Morris [38] has been proven useful in other elicitation studies where the number of proposals from each participant was not fixed [41, 43]. This left us with 122 signs. Subsequently, we conducted a qualitative content analysis following flexible coding approaches [15, 30, 65]. These build on Grounded Theory to code data, but differ from it by taking into account modern tools that allow for a simpler arrangement of data, and in turn for more rigorous and flexible analysis. In contrast to Grounded Theory where small codes are merged into bigger concepts, one starts by coding big indices of data and gradually refines them. In our analysis, we classified each of the 122 user-defined signs based on the following dimensions: Body parts, input modality (adapted from [21]), complexity [55], input area (adapted from [52]), form and flow [55, 77]. We report on those dimensions for contextualization in the results section.

4 RESULTS

In the following, we investigate what signs the participants have defined. We start with an overview of what body parts, input modalities, and locations are preferred for interaction. Next, we analyze more closely what are the preferred signs for each referent, with free hands or hands occupied, and identify what strategies are used for controlling robot motion. Finally, we discuss what are main sources of inspiration that the participants drew from when defining signs.

4.1 Taxonometric Breakdown: Body Parts, Input Modalities, and Input Areas

Body Parts. Figure 3 depicts the distribution of body parts that participants have used for producing the signs. Even though participants could use any body part for interaction, they most frequently suggested using the upper limb (47 %), with fingers and hands used in 31 % of all signs, and arms used in 16 %. This confirms findings from the literature on interaction with off-body robots [47, 51, 59]. This was followed by head and eyes (17 %). The directional mobility

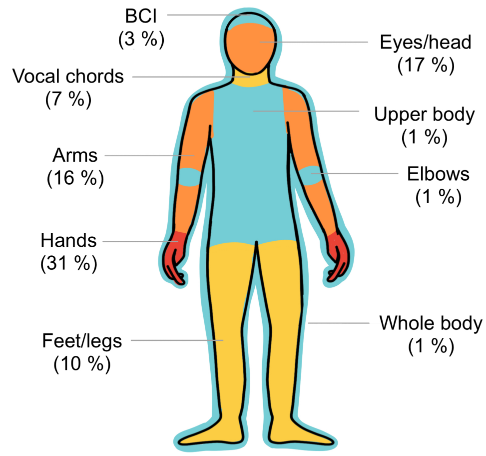

Figure 3: Body parts used for the user-defined signs. Most frequently used are fingers/hands, then arms and eyes/head.

of the head and eyes make them a potentially useful alternative for settings where users cannot or do not want to use their hands. The lower limbs (feet and legs) were used in 10 %.

Input Modalities. To code the input modalities, we used Hertel et al.'s taxonomy for AR [21], as it best reflects all multimodal inputs that occurred in our study, whilst most other taxonomies are bound to specific technologies, or were too coarse to capture our needs. We categorized input modalities either as 'Touch' (contact between any type of surface and a body part), 'Gaze' (directional indications through eye or head motions), 'Gesture' (uninstrumented motion of a body part which is neither 'Touch' nor 'Gaze'), 'Voice', or 'Brain-Computer Interaction (BCI)'. We summarize signs that involve various classes as 'Mixed'. Our results show that the majority of user suggestions for all referents either involve a contact with a surface ('Touch', 36 %) or uninstrumented body motions ('Gestures', 38 %). Touch was primarily performed with hand motion (58 %), but also with the arm (17 %) or with feet or legs (16 %). Gestures were mainly performed with arms (27 %) or hands (26 %), and less frequently with head or eyes (13 %), or feet or legs (9 %).

However, the frequency of input modalities strongly varies for referents. Figure 4 depicts for each referent the percentage of all user-defined signs that belong to one input modality, separately for hands-free and hands-occupied settings. We see that 'Touch' is particularly dominant for *basic control*, and *handling emergencies*, particularly when hands are free. In contrast, 'Gesture' is dominant for *robot motion* and *object manipulations*.

'Gaze' is suggested frequently for *robot motion* (> 17 %) and PICK UP (23 – 44 %). Contrary, the use of 'Voice' was mostly suggested as a modality to handle emergencies, or as an abstract method to activate or deactivate the robot (9 % each). Surprisingly, abstract sounds were also frequently suggested for translatory and rotational motions of the robot (9 % – 17 %).

A distinct property of WRAs is that they can support the user also in settings where their hands may be occupied, for instance by holding an object, or when working with tools. This implies that for such settings, additional constraints need to be met: Any sign

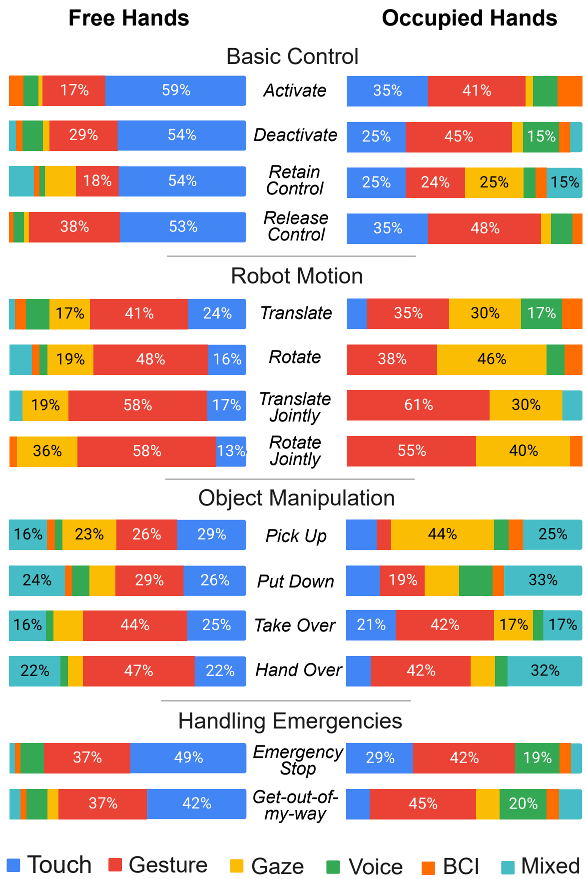

Figure 4: Distribution of input modalities for each referent, divided by hands-free and hands-occupied. 'Touch' and 'Gesture' are frequently suggested when hands are free. 'Gesture' and 'Gaze' often replace 'Touch' when hands are occupied.

must be compatible with the user's manual activity. To investigate preferred interactions under this constraint, we split the set of user suggestions into a subset of signs compatible with occupied hands.

When hands are occupied, signs involving 'Touch' are frequently replaced by 'Gesture', particularly so for those referents that have shown very frequent use of 'Touch' in hands-free. Also 'Gaze' is considerably more frequently used when hands are occupied, particularly for controlling robot motion and for picking up objects.

Input Areas. We analyzed the location of touch contact for the 'Touch' modality: on-robot (touching the robotic arm, gripper, or the harness), on-body (two body parts touching each other), on-surface (touching any passive surface, e.g., the cube, table, or the floor) or on-device (touching any external device). Figure 5 shows the distribution of input areas for 'Touch'. By far most 'Touch' instances were performed on-robot (45 %). Lastly, on-surface (e.g., tapping on the cube) and on-body (e.g., clapping the feet against each other) were frequently used input areas (20 – 23 %). External devices (11 %) were rarely suggested.

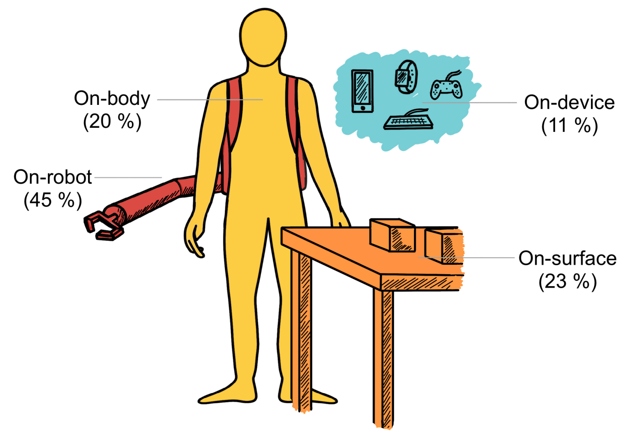

Figure 5: Input areas of user-defined 'Touch' signs. Most frequently suggested is input on the robotic arm, least frequently interactions with external devices.

4.2 Preferred Signs

We gauged user preference in more detail by asking participants to select one preference for each referent (out of the unlimited set of their propositions) for both, hands free and hands occupied. Table 2 lists the 3 most preferred signs for each referent when hands are free and when hands are occupied. To identify the level of consensus between participants' suggestions, we calculated agreement rates for all suggestions using the modified agreement rate introduced by Vatavu et al. [70]:

$$AR(r) = \frac{|P|}{|P|-1} \Sigma_{P_i \subseteq P} \left(\frac{|P_i|}{|P|}\right)^2 - \frac{1}{|P|-1}$$

Here, r refers to the referent for which we compute the agreement rate $AR(r)$, P is the set of all signs elicited for r, and P_i is the i^{th} subset of identical signs in P. The results are shown in Table 2. Agreement rates ranged from 0.02 (low agreement, AR $\leq$ 0.1) to 0.35 (high agreement, 0.3 $\leq$ AR $\leq$ 0.5). The rather low agreement rates are a natural result of the unlimited gesture production and emphasize the exploratory character of the study. Despite the rather low agreement rates of the suggested signs, we observe that participants share considerable agreement on what signs they prefer. We now present the most frequently preferred signs:

4.2.1 Basic Control. Referents for basic control of the robot's functionality comprise ACTIVATION, DEACTIVATION, RELEASE CONTROL and RETAIN CONTROL. For free hands, the most preferred sign for all four referents is a discrete, static touch of the robotic arm, performed either with the finger or the full hand (43 %). It resembles a conventional touch gesture on or with a device. Other preferred options in the top 3 rankings involve basic, discrete actions like clapping or blinking with the eye (both 14 %), which were chosen because of their ease, speed, and comfort.

When hands are occupied, participants tend to replace touch-based interaction by abstract signs. All these signs have in common that they do not require exhaustive body motions, but are simple and fast. For instance, to activate the robotic arm, 21 % of the participants prefer to make a sound with the vocal chords, whereas

	Free Hands		Occupied Hands	
Referent r	$AR(r)$	**Top 3 Signs**	$AR(r)$	**Top 3 Signs**
Activate	0.07	Tap robot with hand (43 %) Clap hands (14 %) Blink with eyes (14 %)	0.06	Make sound with vocal chord (21 %) Blink with eyes (14 %) Brain signal (14 %)
Deactivate	0.08	Tap robot with hand (21 %) Make sound with vocal chord (7 %) Brain signal (7 %)	0.04	Make sound with vocal chord (14 %) Brain signal (14 %) Blink with eyes (7 %)
Release Control	0.03	Tap robot with hand (21 %) Do task oneself, robot takes over automatically (14 %) Clap with hands (14 %)	0.04	Stamp with one's foot (14 %) Look at two objects sequentially (7 %) Stare at object, nod to confirm (7 %)
Retain Control	0.04	Tap robot with hand (29 %) Clap hands (7 %) Stamp with one's foot (7 %)	0.06	Stamp with one's foot (36 %) Clap feet against each other(14 %) Shake head (7 %)
Translate (Object held by robot)	0.05	Robot follows arm at fixed distance (14 %) Use the hand to drag the robot to target (14 %) Robot imitates directional motion of head/eyes (7 %)	0.06	Robot imitates directional motion of head/eyes (21 %) Robot moves one unit per head tilt (7 %) Map vocals to directional motions (7 %)
Rotate (Object held by robot)	0.09	Gripper imitates tilting of fingers/hands (43 %) Gripper rotates one unit per hand tilt (7 %) Rotate index finger for rotation, point to gripper target mid-air to yaw or pitch (7 %)	0.21	Robot imitates directional motion of head/eyes (21 %) Robot imitates directional motion of foot/leg (14 %) Map vocals to rotational directions (7 %)
Translate (Object held jointly)	0.12	Follow user's lead propagated through object (36 %) Use free hand to drag the robot to the target (21 %) Robot imitates directional motion of head/eyes (14 %)	0.23	Follow user's lead propagated through object (43 %) Robot imitates directional motion of head/eyes (14 %) Robot imitates directional motion of upper body (7 %)
Rotate (Object held jointly)	0.18	Follow user's lead propagated through object (36 %) Gripper imitates tilting of free hand (21 %) Gripper imitates tilting of head (14 %)	0.35	Follow user's lead propagated through object (43 %) Robot imitates tilting of head (14 %) Robot imitates tilting of foot/leg (7 %)
Pick Up Object	0.05	Robot follows arm at fixed distance, open/close hand to open/close gripper (21 %) Use hand to drag robot close to the object (7 %) Touch object (7 %)	0.09	Stare at object (14 %) Stare at object, nod to confirm (7 %) Stare at robot and object sequentially (7 %)
Put Back Object	0.02	Robot follows arm at fixed distance, open/close hand to open/close gripper (14 %) Use hand to drag robot to target and tap robot (7 %) Touch target (7 %)	0.10	Make sound with vocal chord (14 %) Move robot to target with hand/eye motions, blink eyes to open gripper (7 %) Stare at target, blink eyes to confirm (7 %)
Take Over Object from Robot	0.03	Robot follows arm at fixed distance, open/close hand to open/close gripper (14 %) Hold free hand out open (14 %) Stare at target (14 %)	0.04	Hold free hand out open (21 %) Stare at target (7 %) Pull cube out of gripper (7 %)
Hand Over Object to Robot	0.02	Robot follows arm at fixed distance, open/close hand to open/close gripper (21 %) Shake object (14 %) Stare at object (7 %)	0.04	Shake object (21 %) Stare at object (7 %) Stare at robot and object sequentially (7 %)
Emergency Stop	0.07	Touch robot with the hand (43 %) Move hand in robot's way w/o touching it (29 %) Make sound with vocal chord (14 %)	0.06	Make sound with vocal chords (29 %) Stamp one's foot (29 %) Move whole body back (14 %)
Get-out-of-my-way	0.07	Push robot away with the hand (43 %) Wave hand aside mid-air ('go away') (14 %) Tap robot with the hand (7 %)	0.05	Shake head (14 %) Make sound with vocal chords (7 %) Rotate upper body (7 %)

Table 2: The table contains the agreement rates and the 3 most preferred signs for each referent (1) when hands are free and (2) when hands are occupied. For each sign, we additionally indicate the percentage of people who preferred this sign in brackets.

others suggest to resort to direct BCI. To release and retain control, participants preferred to stamp with one's foot onto the ground (14 % and 36 %), similarly how stamping can signal a human to stop. Further, we observe that the use of eye gaze, such as staring at one or multiple objects, is a frequently occurring pattern for RELEASE CONTROL to signal the robot to work autonomously on the object(s).

4.2.2 Robot Motion. This group includes TRANSLATE, ROTATE, and their human-robot collaborative counterparts TRANSLATE JOINTLY and ROTATE JOINTLY. The most preferred signs for all referents in this set involve kinemimic motions. These are direction inducing body motions which the robot follows; e.g., if the user's hand moves to the right, the robot also moves in this direction. The most preferred body parts are the hand and the arm (> 50 % for all 4 referents in hands-free). For TRANSLATE, participants prefer that the robot continuously follows their arm at a fixed distance or they manually drag the robot to the desired position (14 % each). For ROTATE, the robot's gripper should mirror the rotations of the human hand (43 %). People particularly expressed the superiority of using hands and arms over other body parts like head or eyes, and feet or legs: "[using the hands,] that's where you can give the most information. [One] can tell how fast, how slow, how far [the WRA should move]" (P7), "when you move your head, you do not see what's here" (P2), "[using the foot] makes me instable" (P7).

Whilst hands were dominant for hands free, they were replaced in hands-occupied settings by body parts with similar mobility. For TRANSLATE and ROTATE, at least 21 % of participants preferred to use the head. For TRANSLATE JOINTLY and ROTATE JOINTLY, users prefer to mediate the motion through the object which they hold jointly with the robot (36 % each). This strong user preference emphasizes that moving the robot through motions which are mediated through a jointly carried object is a desirable input strategy.

4.2.3 Object Manipulation. The set of object manipulations involves PICK UP, PUT DOWN an object, and their collaborative counterparts TAKE OVER FROM ROBOT and HAND OVER TO ROBOT. More than half of all suggested signs (56 %) are composed of at least two separate actions, for instance one action to move the robot to the target followed by a second action to make the robot use the gripper or to confirm the selected target. In contrast, other proposed actions are atomic, such as touching, pointing, or staring at the target. The most preferred sign for all four referents is to manually navigate the robot to the target, followed by using one's hand to mimic how the robotic gripper opens and closes (14 – 21 %). For TAKE OVER FROM ROBOT, atomic actions were equally preferred, such as holding the non-dominant hand out open while waiting for the robot to put the object into the hand (14 %).

Whilst the most preferred signs mainly involve composed hand and arm motions when hands are free, participants preferred atomic signs performed with the head or eyes when hands are occupied. For PICK UP, for instance, users preferred staring at the object of interest (14 %) and variations similar to this command, such as confirming the selection through nodding or staring at the robot after selection (7 % each). For PUT DOWN, 14 % preferred making a sound with the vocal chords.

4.2.4 Handling Emergencies. Referents to handle emergencies involve EMERGENCY STOP and GET-OUT-OF-MY-WAY. Similar to *basic control*, the most preferred signs for *handling emergencies* involve a touch of the WRA (43 % each). However, for EMERGENCY STOP, the sign is a more intense and aggressive touch, usually done with the entire hand that clearly signals the robot to stop moving. In contrast, the touch for GET-OUT-OF-MY-WAY tends to dynamically push the robot away in the opposite direction of its movement.

For hands-occupied, these signs were frequently replaced by foot motions, head motions, or the use of voice. The most preferred signs for EMERGENCY STOP are using vocal chords and stamping (29 % each). For GET-OUT-OF-MY-WAY, shaking the head (14 %) was slightly more preferred than the use of voice (7 %). Another strategy was to reposition or rotate one's own body to rapidly move the robot out of the critical area, such that the robot "does not have the reach" (P3). Whilst the other suggestions would be also applicable to off-body robots, this strategy is specific for body-worn robots.

4.3 Controlling Robot Motion

Human-robot interaction can comprise different levels of human control and robot autonomy. We observed that most signs suggested for *basic control* and *handling emergencies* comprise high-level user commands. These require the robot to understand and take action accordingly, such as automatic motion and path planning. Contrary, we found an outstanding variety of user strategies with varying levels of user control for *robot motion* (TRANSLATE, ROTATE, TRANSLATE JOINTLY, ROTATE JOINTLY). To better understand the preferences, we clustered the suggested signs for *robot motion* based on their underlying concepts. This led to five main strategies illustrated in Figure 6: dragging, body remapping, body relocation, device-mediated control, and targeting. We detail on these in the following:

Dragging. Dragging contains 22 % of all signs in the motion set. Dragging allows for direct control, as the user physically grabs an object with the hand and drags it onto the desired position. We distinguish between two types of dragging:

1. *Robot Dragging* (7 %): The user grabs the WRA with their hand and physically drags it to the target. This allows the user to have direct control of the robot and the object, while avoiding touching the (hot, dangerous, slippery, . . .) object, or the need to carry the load of a heavy object.
2. *Object Dragging* (15 %): This strategy applies to situations in which the user and the robot jointly hold and move an object. With the hand holding the object, the user pushes or pulls the object in the desired direction, whilst the robot follows accordingly. In case the object is heavy, users additionally wished for the robot to take the main physical load of carrying the object, while they only provide indications through slight directional forces applied to the object.

Body Remapping. Body remapping is the most frequently suggested strategy, containing 53 % of all suggested motion-related signs in total. It allows for direct control, as motions of a body part are directly mapped to the motion of the robotic arm. We can further divide body remapping into the following sub-categories:

1. *Imitation* (7 %): The user moves their dominant arm and expects the robot to imitate their arm motions by following it at a fixed distance. This allows the user to continuously control the robot; however, the distance at which the robot follows the user must be determined prior to the interaction. This mapping also limits the robot motions of the robot to the distance covered by the user's arm reach.
2. *Continuous Remapping* (40 %): The user continuously moves a body part, such as the foot, the head, or the upper body, whilst the robot maps the motions accordingly. In contrast to the previous strategy, however, the participants did not expect the robot to act on the same scale as the indicated body motions. Consequently, this requires that the scale must be defined by the user prior to the interaction.

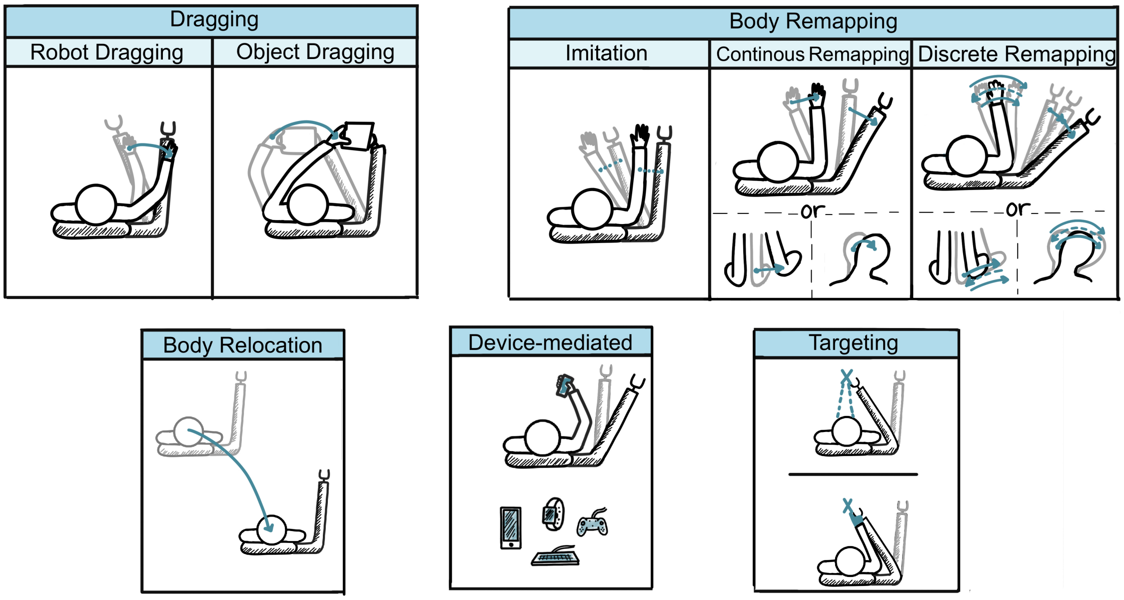

Figure 6: We identified five strategies to control robot motion, ranging from direct physical control of the robot's motion (*dragging*) to high-level selection of the desired target (*targeting*).

(3) *Discrete Remapping* (6 %): This strategy is the discrete counterpart of *continuous remapping*. Here, the robot moves one unit, e.g., per hand swipe or head tilt in the indicated direction. As these discrete indications are less similar to how humans naturally move than continuous indications, this strategy has been less frequently suggested. However, it offers unique benefits for fine-grained control of the robot's position and orientation.

Body Relocation. Body relocating is a strategy specific for on-body robots. The user moves or rotates one's own body to move or rotate the robot, respectively. With this strategy, the human has the highest level of possible control since there is no active robotic motion involved. Beside using body relocation to move the robot for coarse navigation, some participants also suggested it to handle emergency situations. As suggested by one participant, body relocation is most suited for coarse motions and longer distances in horizontal directions. However, as the body's natural vertical reach is limited, the control over moving the robot up and down on a bigger scale is limited. These restrictions might explain why this strategy was only rarely suggested (2 %).

Device-mediated Control. Seven percent of all suggestions involve using an external device as a controller for robot motion. Suggestions comprised a portable joystick, a smartwatch, smartphone, or a remote control. Hereby, users indicate directions, e.g., through directional swipes or buttons which are mapped to directions. This strategy is easy to use because users are already familiar with it, e.g., from gaming consoles, and is commonly implemented for the control of robotic arms [1, 16, 44]. However, this strategy may be the result of some legacy bias. It must be noted that mapping from (usually) two-dimensional input onto three dimensions of robot movement is less direct and desirable than other strategies.

Targeting. Four percent of all suggestions are discrete, deictic signs, either executed through pointing to the target or by eye gaze. Since the user selects the target, but leaves path and motion planning to the robot, this strategy requires the highest level of robot autonomy. This allows for quick user commands which might be helpful in situations where the user is busy with another primary task. However, *targeting* has limitations to indicate a point of interest in 3D. The raycasting model underlying indirect pointing or gaze is limited by occlusions and potential ambiguities. In contrast, direct touch-contact pointing to a location in 3D is non-ambiguous, but restricted by the user's arm reach. Although first approaches to enrich gaze with depth information to control a robotic arm already exist [60], the strategy remains challenging for 3D motions.

4.4 Sources of Inspiration: Devices, Body, and Other Beings

A closer analysis of the suggested signs and participants' reasoning underlying their choice revealed three main sources of inspiration, which apply for both hands-free and hands-occupied situations: the interaction with already known devices, the naturalness of body motions, and the intuitiveness of interacting with other beings.

4.4.1 *Transferring Device-Specific Metaphors onto the Robot.*

Many suggestions involved signs performed on the robot, as the robot's proximity to the body makes them comfortable. People tend to combine these physical affordances of the WRA with known interactions from other devices. We found that this combination makes the interaction with the robot easy to use and remember. Specifically, we observed that touching the robot in the context of *basic control* was commonly associated with pressing a button or a touch sensor on the robot: "just like a phone" (P6) or "like a remote control" (P14). Similarly, for *handling emergencies*, several participants suggested touching the robot to stop and compared this to sliding a hand in-between closing elevator doors (P2) or in-between a closing car window (P1), which would stop automatically as soon as they detect a human hand.

4.4.2 Mapping Body Motions onto the Robot. Participants leveraged the ease and directness of body motion for controlling the robot, particularly for referents within *robot motion* and *object manipulation*. Participants explained that a mapping of body motions to the robot improves the feeling of control, as it feels "like [their] hand was the robotic arm" (P12). Ten participants explicitly stated that the intuitiveness and naturalness of using one's own hand makes this type of interaction particularly easy to learn and use.

4.4.3 Inspiration from Human-Human and Human-Animal Interactions. If not preferred to control the robot through body remapping, many gestures for collaborative tasks were inspired by real-life interactions with people or pets. For instance, to hold the hand out open or move the object close to the robotic gripper resembles how one would hand or take over an object from another human: "just like for normal people. When I give something to a colleague: I hand it over to him [...] and he just takes it in his hand" (P9). To handle emergencies, many participants took inspiration from their human instinct to push an object away when it gets into the way, or to generate an audible warning signal (through stamping or vocalization) "which is a human sign because one also knows stamping when something should stop" (P9) or "like scaring away a cat" (P1). Similarly, signs such as pulling an object out of the robot's gripper and shaking the object were associated to a playful experience with a dog, indicating "here is your toy" (P3).

5 DISCUSSION AND DESIGN IMPLICATIONS

From the above quantitative and qualitative findings, we derive the following implications for the design of interactions with a WRA.

5.1 Input Modalities and Gestures

The study results show versatile strategies of interaction with a WRA, including touch, gesture, gaze, and voice. However, two modalities clearly stand out: touch and mid-air gestures. Firstly, touch is predominantly suggested for basic control and handling emergencies, and most frequently performed on the robotic arm. The design of touch interactions that are easy to use and remember can draw inspiration from existing devices, but also from tactile interaction with human collaborators. It is noteworthy that the proposed touch interactions are of rather coarse-grained character, implying they can be performed when wearing gloves. Secondly, mid-air gestures are dominating for controlling robot motion and manipulating objects. Here, our study results show a broad variety of strategies to navigate the robot. These range from discrete, high-level actions (e.g., pointing at the target), to continuous interaction with a high level of control and specific for on-body robots (e.g., moving one's own body to relocate the body-worn robot for coarser motions). The most frequently suggested technique, however, involves remapping one's own body motions to robot movement. Such direct remapping makes robot control very easy as it is based on natural human behavior: The naturalness of mapping learned motor motions onto other body parts is a well-studied phenomenon in neuroscience research [64]. Lastly, to move an object together with the robot, the easiest technique is that the robot follows the user's lead which is propagated through the jointly held object.

In cases when both hands are occupied by the primary task, sounds (e.g., through voice or stamping one's foot) are preferred for basic control and in emergency situations, whereas head and eye gaze is a preferred input technique for robot motion.

In consequence, we can cover a large subset of referents with at least one of the 3 most preferred signs by combining touch and gaze as input modalities. This accounts for all referents when hands are free and for 11 out of the 14 referents when hands are occupied.

5.2 Robot as Extension of the User's Body

It is noteworthy that many of the proposed signs share similarities with interactions already known from off-body robots, such as tactile interactions [10], or body remapping for controlling drones, e.g., [47]. This suggests it may be possible to establish a common gesture language for off-body and on-body robots, an interesting question for future work.

However, our results also highlight important differences between robotic arms that are worn on the body and those that are not: the WRA moves together with the human body, no matter whether the user intends it or not. This calls for different modes of how the robot can respond to body movements. First, the robot's end effector could be *fixed in space*, such that its world coordinates do not change when the user moves. This is important for construction or assembly tasks where the robot needs to operate at a fix location or steadily hold an object while the user moves about for a primary task. Alternatively, the robot's end effector could be *fixed on body*, such that its world coordinates change along with the user's body movements. The latter can be used as a fast and direct means for moving the robotic arm, by rotating one's upper body, by stepping side-ways, or leaning forward and back. We anticipate this will be particularly helpful for coarse and rapid robot motion that provides a spatial reference, whilst the precision of robotic actuation is better suited for fine motion as required in precise manipulative actions. This asymmetric division of macrometric and micrometric control resembles a serial assembly of two motors as discussed by Guiard and allows to extend the kinematic chain model he proposed for bimanual interactions accordingly, through a chain formed of the human body and the robotic arm [19].

It is a well-known phenomenon that wearable devices, tools, and objects might map to the user's body schema after a prolonged use and are perceived as an extension of the own body [6, 37, 42]. Participants' quotes (e.g., "as if [their] hand were the robotic arm" (P12)) and suggested strategies (e.g., shifting the body to move the robotic arm) suggest that also the WRA could ultimately be perceived as an extension of users' own bodies, given that interactions are designed naturally. However, the extent to which this is desirable from a user-perspective remains subject of future studies.

5.3 On-Body Robots as Tool and Collaborator

Our findings demonstrate that on-body robots can and should take a different role depending on the task. This comprises the role of a collaborator which is able to react to high-level commands without requiring further user guidance, able to understand implicit clues (e.g., removing a cube out of the robotic gripper to make it stop building the tower), or to learn user-specific behavioural patterns over time. But the robot can also take the role of a purely functional tool which allows for precise and direct control, not involving any intelligent decisions or automatic behaviour. Our observations confirm prior discussions in literature that these roles are not exclusive, or binary. Rather, the robot should act on a spectrum of autonomy [39, 63]. Participants of our study have even suggested signs, which combine both collaborative and purely functional traits. An example comprises manually dragging the robot towards the object, followed by holding it there for some time to 'show' the object to the robot, expecting the robot to understand it should pick up the object on its own. These non-exclusive design patterns for the interaction with on-body robots might allow designers to overcome prevailing, purely functional vs. anthropomorphism- or zoomorphism-inspired design strategies [20], and ultimately create interactions that are in-line with the hybrid character of WRAs.

5.4 Sensing Interactions with WRA

The interactions proposed by participants of our study can be captured using various sensor technologies, either deployed on the robot, or on the user, or both.

Augmenting robots with a sense of touch, through buttons or touch sensors up to interactive skin covering the full robot, has been of interest for a long time [10]. For our suggested touch interactions, a low resolution touch sensor matrix which is attached around the robotic arm and easily reachable for the user is sufficient. Hereby, we could use a capacitive sensor matrix, e.g., as suggested in [68]. Adding continuous force sensing, instead of touch contact alone, allows for capturing directional forces. Alternatively, motions which involve coarse-grained forces exerted on the robotic arm, such as dragging the robot onto the desired position, can also be sensed by torque sensors deployed inside the joints of the robot.

Various signs within the top three of both hands-busy and hands-free conditions involve discrete gestures, such as opening and closing the fist, rotating the hand, or stamping. These can be captured using body-worn sensors. Notable examples include vision-based approaches with body-worn cameras [9, 24, 25], sensing with Inertial Measurement Units [76, 80], or through EMG signals [46, 67]. To track continuous limb motions, such as translatory or rotational motions of the hand, arm, head, or foot which the robot should mimic, IMUs are a straightforward choice. However, the pure use of IMUs attached to the user's body is not suited for precise control control because of accumulating errors and delays [56]. Here, vision-based approaches are most promising.

It is still an open research issue to reliably detect gestures and limb motions only through robot-integrated sensors [4], and detecting gaze is even more demanding. We can, however, expect that with technological advances, user's limb motions can be accurately captured through robot-integrated fish eye cameras or radar. Also, given the robot is mounted on the body, it may be able to detect body motions with built-in IMUs, just from the way it moves with the body. Future research should investigate robot-deployed technologies for sensing user interactions, to ease the ergonomic deployment of WRAs for everyday activities.

5.5 Limitations

In our study setup, participants stood in front of a table in a quiet environment. The preferred signs and interaction strategies might vary when interacting with the arm whilst moving, sitting, or with external bystanders nearby. This should be subject to future studies.

We used a light-weight, passive WRA prototype, which was manually moved either by the experimenter or the participant. Although the prototype fulfills common design characteristics of a WRA in terms of mounting location, dimensions, and workspace, its non-functionality might have influenced participants' behaviour as they did not need to fear any unexpected behavior and were not confronted with the true strength and speed of a WRA. Also, the exact way a sign is executed might vary with the WRA's detailed link-and-joint-based structure. Whilst this might affect the WRA's joint space and the angle at which the end effector is approaching a target, the absolute position of the end effector and the user's overall goals, physical abilities, and preferences stay the same. Thus, we believe that our results generalize to more complex WRAs. Furthermore, the WRA was designed to have a reach similar to that of a real human arm. Signs might vary for controlling a robotic arm with an extended reach or one designed for microscopic manipulation.

We opted for abstract cubes instead of concrete objects to get a principled understanding of underlying models and interaction strategies that generalize beyond a specific application domain. Similarly, we chose domain-agnostic referents which can be transferred to various application cases with physical objects. Evaluating the individual effects of different object sizes, weights, and affordances are beyond the scope of this study and subject to future work.

During our study, we observed that our prototype occasionally hindered movements of the human arm and vice versa. Our study did not investigate this aspect further. Future work should discuss strategies to resolve such collisions in a shared workspace, including considerations of where the WRA should be attached to the body.

Lastly, our results showed that BCI was a rarely suggested input modality. This might be a consequence of our study method, as unlike gestures, users cannot demonstrate BCI to the experimenter easily. The extent to which BCI is a desirable technique to control a third, robotic arm should be investigated in future work.

6 CONCLUSION

This paper contributed findings from the first elicitation study for the interaction with WRAs. We systematically investigated user preferences when hands are free and occupied and provided a comprehensive list of signs preferred by the participants. Our analysis revealed that overall users prefer mid-air gestures performed with hands and arms to navigate the robot and manipulate objects, and on-robot hand gestures for all other tasks types, such as physically pushing away the robot in an emergency. When hands are occupied, users generally preferred sounds for basic control and in emergency situations, such as stamping, whereas they proposed head and eye gaze as a desirable mitigation strategy to navigate the robot. When user and robot jointly hold an object, it was found most desirable to control the robot by moving the object and expecting the robot to follow the user's lead. Our findings reveal three main sources of inspiration. For basic control, inspiration can be drawn from the interaction with existing devices. To handle emergencies and for collaborative tasks, interactions can be inspired by human-human interaction, whereas body motion is a natural way to steer the robot. Our findings also confirm that body-worn robots should offer different levels of autonomy which range from directly controlling the robot like a tool all the way to collaborating with an intelligent partner that is able to understand high-level commands or even implicit cues. We derived various implications for sensing technology, which can be deployed on the robot, or on the human user. We see our findings as a first step toward immersive interactions with WRAs that reflect on user's behavior. Future research can use our results as a starting point to understand how WRAs should be designed to best support users in their daily lives.

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A STUDY DETAILS

Before starting the study, we introduced the participants to Wearable Robotic Arms and the goal of the study by reading out the following text:

> *"A Wearable Robotic Arm is a device that is attached to your body and can act like a third hand that helps you in everyday life. Imagine, e.g., a scenario where your hands are busy holding some packages whilst you need to open a door, or you are cooking and need to move a hot dish. A robotic arm might support you in such situations. We aim to understand how people would want to control and interact with such a wearable robotic arm. However, in our study, we don't consider real-life scenarios such as the ones mentioned, but a more abstract setting where we use cubes for interaction. The cubes are chosen as neutral representations of our real-world examples."*

Below, we list the descriptions that we read out to the user.

Task 1: Activation. The robot is in standby mode and must be activated before it can follow any commands. How would you activate the robotic arm?

Task 2: Deactivation. The robot is activated. You want to deactivate it to make it go back into standby mode. How would you deactivate the robotic arm?

Task 3: Translate. The robot is activated and holds a cube. You want to move the cube to this position *(position was demonstrated by the experimenter)* on the left/right, forward/backward, upward/downward. How would you instruct it to do so?

Task 4: Rotate. The robot is activated and holds a cube. You want to rotate the robotic arm by this angle *(position was demonstrated by the experimenter)* clockwise/counter-clockwise, forward/backward, left/right. How would you instruct it to do so?

Task 5: Pick Up Object. The robot is activated. There are several white cubes and one marked one on the table. You want the robot to pick up the marked cube. How would you instruct the robotic arm to pick up the object for you?

Task 6: Put Back Object. The robot is activated and holds a cube. You want the robot to place it down somewhere on the table. How would you instruct the robotic arm to do so?

Task 7: Translate Object Jointly. The robot is activated. You are holding the big cube in your left hand together with the robotic arm. You want to jointly move the robotic arm to this position *(position was demonstrated by the experimenter)* on the left/right, forward/backward, up/down. How would you instruct the robotic arm to jointly move the object to these positions?

Task 8: Rotate Object Jointly. The robot is activated. You are holding the big cube in your left hand together with the robotic arm. You want to jointly rotate the robotic arm by this angle *(position was demonstrated by the experimenter)* clockwise/counter-clockwise, forward/backward, left/right. How would you instruct it to do so?

Task 9: Take Over Object From Robot. The robot is activated and holds a cube. You want the robot to hand it over to your left hand. How would you instruct the robotic arm to do so?

Task 10: Hand Over Object to Robot. The robot is activated. You are holding a cube in your left hand. You want the robot to take over the object. How would you instruct the robotic arm to do so?

Task 11: Release Control. The robot is activated. Your goal is to get a tower of cubes where all cubes on the table are stacked one onto the other. However, this is a tedious task and you want the robotic arm to do the work for you autonomously. This means the robotic arm should stack the cubes without your help all by itself. The robot knows the task of building a tower out of cubes. Furthermore, it knows where all cubes are located on the table and how to move and stack them. How would you make the robot start stacking the cubes autonomously?

Task 12: Retain Control. The robot is activated. The robot is stacking cubes on the table autonomously. However, you want the control over the robot back such that it stops working by itself but listens to your commands again. How would you instruct the robot to stop working autonomously?

Task 13: Emergency Stop. The robot is activated. There is a stack of cubes on the table. The robot is in autonomous mode and suddenly moves into the direction of the cubes, risking knocking over the stack. You want it to stop immediately. How would you instruct it to do so?

Task 14: Get-out-of-my-way. The robot is activated and is moving in front of your face, blocking parts of your view as it is invading your workspace. You want the robotic arm to move out of your way. How would you instruct it to do so?