Understanding Wheelchair Users' Preferences for On-Body, In-Air, and On-Wheelchair Gestures

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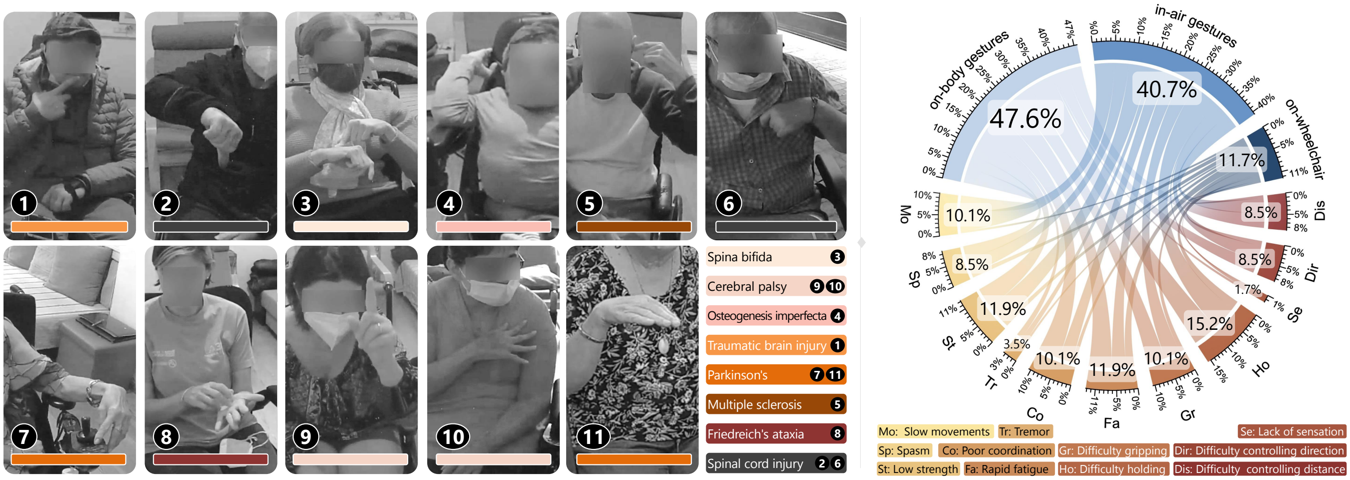

Figure 1: Examples of *on-body*, *in-air*, and *on-wheelchair* gestures performed by wheelchair users in our gesture elicitation study (left) and the relationship between their gesture preferences and self-reported motor impairments (right). *Note:* the ribbon widths from the right chart encode the strength of the relationships between gesture types and motor impairments, e.g., 5.6% of the *on-body* gestures elicited in our study were proposed by users that reported low strength (St).

ABSTRACT

We present empirical results from a gesture elicitation study conducted with eleven wheelchair users that proposed *on-body*, *in-air*, and *on-wheelchair* gestures to effect twenty-one referents representing common actions, types of digital content, and navigation commands for interactive systems. We report a large preference for *on-body* (47.6%) and *in-air* (40.7%) compared to *on-wheelchair* (11.7%) gestures, mostly represented by touch input on different parts of the body and hand poses performed in mid-air with one hand. Following an agreement analysis that revealed low consensus (≤5.5%) between users, although high perceived gesture ease, goodness, and social acceptability within users, we examine our participants' gesture characteristics in relation to their self-reported motor impairments, e.g., low strength, rapid fatigue, etc. We highlight the need for personalized gesture sets, tailored to and reflective of *both* users' preferences *and* specific motor abilities, an implication that we examine through the lenses of ability-based design.

CCS CONCEPTS

• **Human-centered computing → Gestural input**; **Accessibility technologies**; **Empirical studies in accessibility**.

KEYWORDS

Gesture input, wheelchair users, motor impairments, mobility impairments, motor symptoms, gesture elicitation, study, on-body input, on-wheelchair gestures, mid-air gestures, gesture analysis

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1 INTRODUCTION

Gesture input is widespread in interactive systems, from touch and motion gestures prevalent on smartphones [32,72] and wearables [35] to whole-body gestures used in video games [53] to in-air gestures facilitating interaction in smart environments of diverse kinds [10,48,69,79]. Among their many features, gestures are fast [51], reflective of user natural behavior [96], act as shortcuts with cognitive benefits for users [5], leverage direct access to digital content [74], and facilitate intuitive input for interacting with remote systems via referential pointing [8].

However, gesture input relies on certain assumptions about users' motor abilities to extend and bend fingers, form hand poses, rotate wrists, move arms, aim and touch accurately, and coordinate different parts of the body to produce meaningful movement for robust detection and recognition by a computer. Assumptions such as these create accessibility challenges for people with motor and/or mobility impairments when using gesture interfaces designed for the "average user" [94]. Prior work has documented such accessibility challenges for mobile devices [62,87], wearables [57,58,88], and large displays [64,89]. However, this prior work has focused primarily on touch input due to the prevalence of touchscreen devices, while other types of gestures that can be performed from the space of the wheelchair, such as *in-air* and *on-body* (see Figure 1, left), have been examined to a much lesser extent. Nevertheless, *in-air* and *on-body* gestures may prove more accessible to wheelchair users since they leverage the motor abilities of large muscle groups, different from the accurate aiming and tapping required for touchscreen input [62,64,67,70] and, consequently, feasible under a variety of motor impairments (see Figure 1, right). However, despite the large scientific literature on *in-air* [43] and *on-body* [9] gestures, prior work has primarily addressed users without motor impairments.

To address this gap in design knowledge for accessible gesture input, we examine in this work wheelchair users' preferences for *on-body*, *in-air*, and *on-wheelchair* gestures. We focus on wheelchair users since the wheelchair is one of the most common assistive devices for personal mobility [97], employed by people with diverse levels of functionality (paraplegia, hemiplegia, and tetraplegia) and health conditions [99] and, thus, with diverse motor abilities to use gesture input. Also, wheelchairs can be instrumented with sensors and actuators toward "smart wheelchairs" [49] and enable *on-wheelchair* input via "chairables" [13,14]. Moreover, beyond *on-wheelchair* gestures, the embodiment of the wheelchair [73] as an extension of the user's peripersonal space [25] leverages unique possibilities for *in-air* gesture input, while the seated position facilitates hands to reach the entire body, including the legs, toward more expressive [30] *on-body* input compared to standing up [29,31]. In this context, we make the following contributions:

(1) We present the results of a gesture elicitation study conducted with 11 wheelchair users that proposed *on-body*, *in-air*, and *on-wheelchair* gestures to effect 21 referents representing common actions, types of digital content, and navigation commands for interactive systems, e.g., access email, turn on the TV, etc. We report a large preference for *on-body* (47.6%) and *in-air* (40.7%) vs. *on-wheelchair* (11.7%) gestures, primarily performed with one hand (76.3%) as touch input (34.2%) on the body and hand poses (22.5%) in mid-air.
(2) Following an agreement analysis that revealed low consensus ($AR_\epsilon \leq 5.5\%$) between participants' gesture proposals, we examine the characteristics of the elicited gestures in relation to our participants' self-reported motor impairments, e.g., low strength, rapid fatigue, etc. We highlight the need for personalized gesture sets, tailored to and reflective of *both* users' preferences *and* specific motor abilities.
(3) Based on our findings, we outline nine design implications for *on-body*, *in-air*, and *on-wheelchair* gesture input performed from the space of the wheelchair, which we discuss through the lenses of ability-based design [94,95].

2 RELATED WORK

We relate to prior work on smart wheelchairs that leverage sensing and communications for more accessible navigation in the physical environment. We also overview the scientific literature on *on-body* and *in-air* gesture input where, despite considerable work, the needs and preferences of wheelchair users have been little examined.

2.1 Smart Wheelchairs and Chairables

A large body of work exists on extending the functionality offered by conventional wheelchairs, from making them more comfortable and ergonomic [18,19,63] to designs of smart wheelchairs [49] that leverage sensors, actuators, and artificial intelligence to enable a large palette of interactions from the space of the wheelchair [13, 14,46,76,81,83]. For example, Kutbi *et al.* [46] integrated a Kinect, laptop, wireless router, and tablet device on a wheelchair and used a head-worn video camera to enable navigation via head gestures; Trivedi *et al.*'s [81] smart wheelchair could be controlled with input from either a keyboard, webcam, or microphone; and Singer and Hartmann's [76] See-Thru eye-tracking interface integrated feedback with spatially-arranged LEDs on a wireframe mounted on the wheelchair. Other work has focused on the sensory and motor augmentation of wheelchair users. For example, ExtendedHand [6] used video projections of a virtual hand in the environment, which users could control via a touchpad from the wheelchair armrest. Tsui *et al.* [82] developed Manus ARM, a robotic arm for picking up objects, mounted on the wheelchair and controlled via a touchscreen and joystick mouse. The Vibrotactile Glove [83] was designed to deliver vibrotactile feedback to wheelchair users with visual impairments during the operation of the power wheelchair.

Carrington *et al.* [14] coined the term "chairables" to denote devices designed to fit with the form of the wheelchair and be used from the wheelchair space, and explored possibilities for their placement and form factors. A follow-up work [13] introduced the "Gest-Rest family" of devices that can fit over standard wheelchair armrests to enable gesture input in the form of presses, flicks, squeezes, and punches on the armrest. The results revealed favorable acceptance of Gest-Rest devices, positive appreciation of their always-available nature due to the wheelchair-integrated form factors, but also the need for customizing the device, modality, and gesture set to the specific motor abilities of wheelchair users. Unfortunately, no work followed to understand user performance and preference with *on-wheelchair* input vs. other gesture types, such as *in-air* [43] or *on-body* [9]. Next, we overview prior work on *on-body* and *in-air* gesture input, which has primarily examined the performance and preference of users without motor impairments.

2.2 On-Body Gesture Input

On-body interaction has the advantage of being always available, supported by a large surface that can serve for both input and output, and augmented naturally by proprioceptive and tactile feedback. For example, Harrison *et al.* [29] introduced OmniTouch, a shoulder-worn depth-sensing and video projection system enabling multitouch interaction with everyday surfaces, including the user's hands, arms, and legs. Armura [31] tracks the location and gestural state of the user's arms and hands, on which a ceiling-mounted projector renders coordinated graphical feedback, to enable a variety of single-handed and bimanual interactions. Besides computer vision, other sensing technology has been used to detect on-body input: Mujibiya *et al.* [65] used transdermal ultrasound propagation for forearm gesture input, Matthies *et al.* [59] introduced Botential, an extended on-body input space based on electrical signatures, Ye *et al.* [102] explored near-field enabled clothing, and Xu *et al.* [101] examined on-face interactions sensed with earbuds.

Direct input on the body has also been studied for users with various disabilities. Oh and Findlater [68] conducted a study with twelve participants with visual impairments and reported that the least preferred locations were the face, neck, and forearm, while the hands were considered discreet and natural surfaces for input. A follow-up study [78] extended the results to fifteen locations on the body: ear, shoulder, thigh, wrist, back of hand, five fingers, and five locations on the palm. Malu and Findlater [58] proposed an accessible solution for people with upper-body motor impairments to control head-mounted displays with switch-based input via touchpads positioned on the body or wheelchair. We did not find other work on *on-body* input for users with motor impairments.

2.3 In-Air Gesture Input

In-air gesture input has been extensively studied in the scientific literature for a diversity of applications, including in-vehicle interaction [10], AR [69], home entertainment [79], and mass-computer interaction [48]; see Koutsabasis and Vogiatzidakis [43] for a systematic literature review. Gestures performed in air have also been implemented for wheelchair control and navigation. For example, Kim-Tien *et al.* [42] proposed a camera-based computer vision system, and Kundu *et al.* [45] employed inertial measurement units and myoelectric sensing to detect hand gestures for wheelchair navigation. Unlike these applications that implemented researcher-defined gestures, we are interested in wheelchair users' preferences for and performance with gestures matching their motor abilities. In this area, Vatavu and Ungurean [88] reported results on stroke-gestures and motion-gestures collected with a wearable device, and showed that users with upper-body motor impairments took twice as much time to produce stroke-gestures on wearable touchscreens compared to users without impairments, but articulated motion-gestures equally fast and with similar acceleration characteristics. Ungurean and Vatavu [84] conducted interviews with twenty-one people with motor impairments about their preferences for accessible input modalities for various wearables—smartwatch, fitness tracker, ring, smartglasses, smart earbuds,—and reported equal preferences for *in-air* hand gestures and *chairables* [14].

2.4 Summary

A large body of work exists on *in-air* and *on-body* gesture input, but addressing almost exclusively users without motor impairments. The design knowledge available on accessible gesture input for users with motor and/or mobility impairments has been primarily constituted for touchscreen devices and, in the case of wheelchair users, for *on-wheelchair* gestures performed on the armrest. In this context, more scientific investigation is needed to understand wheelchair users' preferences for other gesture types, including *on-body*, *in-air*, and *on-wheelchair*, which leverage different motor abilities than those required to implement touch input on mobile devices. Next, we present a gesture elicitation study conducted to understand preferences for such gesture types, which we characterize with a diversified set of measures.

3 EXPERIMENT

We conducted an experiment to understand wheelchair users' preferences and perceptions of *on-body*, *in-air*, and *on-wheelchair* gestures to control interactive systems, for which we employed the end-user elicitation method [90,93,96]. The experiment was approved by the Ethics Committee of the University of Suceava.

3.1 Participants

Eleven people (5 male and 6 female), aged between 44 and 66 years old (M=51.5, SD=6.4), participated in our study. Our inclusion criterion was people who were wheelchair users, which we recruited via convenience sampling from a non-profit association providing technical support to people with disabilities. Our participants reported a diversity of health conditions, functionality, and motor impairments, reflected by a wide range of WHODAS 2.0 [98] health and disability scores, between 12.5 and 45.8 (M=33.9, SD=10.7).[1] The most frequently reported motor impairments [23] included difficulty holding (9 of 11 participants), rapid fatigue (7/11), low strength (7/11), slow movements (6/11), poor coordination (6/11), and difficulty gripping (6/11); see Table 1 for details. The number of years since our participants had been living with their motor impairments varied between 8 and 49 (M=26.0, SD=17.5). We had a balanced distribution of wheelchair type in our sample with six participants using manual and five using power wheelchairs.

3.2 Procedure

We elicited participants for *on-body*, *in-air*, and *on-wheelchair* gestures to invoke specific referents for interactive systems, e.g., answer a phone call or access email. To cover a wide range of system functions and types of digital content, we selected 21 frequently used referents from prior work, including from the top-10 most influential gesture elicitation studies [91, p. 860], elicitation studies conducted with people with motor impairments [22,57,104], a study focused on content type [74], content categories used during interviews with wheelchair users for inclusive design [14], and gesture elicitation involving wearables [26,40]. Also, following the design of prior studies [15,41,57,69,72], we grouped our referents in three generic categories: *Actions*, *Content*, and *Navigation*; see Table 2. For each category of referents, participants received the following instructions: "Here is a list of referents. Think about suitable gestures to execute these referents. The gestures should be easy to perform, easy to recall at a later time, and a good fit to

[1] According to the normative data report of Andrews *et al.* [2] based on 8,841 respondents, individuals scoring between 20 and 100 on the WHODAS scale are in the top 10% of the population distribution likely to have clinically significant disabilities.

Table 1: Demographics of our study participants, their self-reported motor impairments described using the eleven categories from Findlater *et al.* [23], and the WHODAS 2.0 [98] health and disability scores.

Participant (age, gender)	Health condition‡	Functionality	Years with imp.	Self-reported impairments†												WHO-DAS score	Wheel chair type
				Mo	Sp	St	Tr	Co	Fa	Gr	Ho	Se	Dir	Dis	#		
P_1 (45, M)	Traumatic Brain Injury	Tetraplegia	25	✓	–	–	–	✓	✓	–	–	–	–	✓	4	45.8	power
P_2 (58, M)	Spinal Cord Injury (T7)	Paraplegia	8	–	–	–	–	–	✓	–	✓	–	–	–	2	41.7	manual
P_3 (48, F)	Spina Bifida	Paraplegia	48	–	–	✓	–	–	✓	–	✓	–	–	–	3	39.6	manual
P_4 (49, M)	Osteogenesis Imperfecta	Tetraplegia	49	–	–	–	–	–	✓	–	✓	–	–	–	2	33.3	power
P_5 (50, M)	Multiple Sclerosis	Tetraplegia	22	✓	–	✓	–	✓	–	✓	✓	–	–	✓	6	39.6	manual
P_6 (66, M)	Spinal Cord Injury (C4,C5)	Tetraplegia	10	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	10	37.5	power
P_7 (54, F)	Parkinson's	Tetraplegia	13	–	✓	✓	✓	✓	✓	✓	✓	–	✓	–	8	37.5	power
P_8 (44, F)	Friedreich's Ataxia	Tetraplegia	8	✓	–	✓	–	✓	–	✓	–	–	–	–	4	14.6	manual
P_9 (48, F)	Cerebral Palsy	Tetraplegia	48	✓	✓	✓	–	–	✓	✓	✓	–	✓	✓	8	37.5	manual
P_{10} (47, F)	Cerebral Palsy	Tetraplegia	47	–	✓	✓	–	✓	–	✓	✓	–	✓	✓	7	33.3	power
P_{11} (58, F)	Parkinson's	Tetraplegia	8	✓	✓	–	✓	–	–	–	✓	–	✓	–	5	12.5	manual
		Summary	**26**	**6**	**5**	**7**	**2**	**6**	**7**	**6**	**9**	**1**	**5**	**5**	**5.4**	**33.9**	

† The code in the parentheses denotes the affected vertebra(e), e.g., "Spinal Cord Injury (C4)" refers to a traumatic injury at the 4th cervical vertebra.
‡ From [23]: Mo = Slow movements; Sp = Spasm; St = Low strength; Tr = Tremor; Co = Poor coordination; Fa = Rapid fatigue; Gr = Difficulty gripping; Ho = Difficulty holding; Se = Lack of sensation; Dir = Difficulty controlling direction; Dis = Difficulty controlling distance; # = number of impairments.

the referents. The gestures can be performed however you want: on your body, including clothes, in air around the body, or on the wheelchair. You are not constrained to use the same type of gestures (on the body, in air, or on the wheelchair) for all of the referents; rather, you should choose the type of gesture you believe is the most appropriate to execute each referent. You can use any hand to perform the gestures." Then, each referent was presented with a short sentence on a computer screen, e.g., "Propose a gesture to answer an incoming phone call;" see the second column of Table 2. The orders of the categories and referents in each category were randomized per participant. The sessions were video recorded.

3.3 Design

Our study was a within-subjects design with one main independent variable, Referent, nominal with twenty-one conditions; see Table 2. We also used the grouping of referents into categories, specified with the Referent-Category nominal variable with three conditions: *Actions*, *Content*, and *Navigation*. The dependent variables are represented by the measures collected from our participants and measures extracted from the videos; see next for details.

3.4 Measures

We characterize our participants' preferences for and articulations of *on-body*, *in-air*, and *on-wheelchair* gestures with a set of ten measures representing the dependent variables in our experiment.

3.4.1 Measures of gesture articulation. We used the video recordings of the study to extract the following information:

- Gesture-Locale with three categories: *on-body*, *in-air*, and *on-wheelchair* gestures.
- Gesture-Locale-Detail represents specific details about each condition of Gesture-Locale. For *on-body* and *on-wheelchair* gestures, we retained the body part (e.g., left ear) and wheelchair part (e.g., right armrest) in relation to which the gestures were performed. For *in-air* gestures, we extracted their location in a system of reference centered on the body with six regions: front, back, left, right, up, down.
- Gesture-Extent was measured in McNeill's [61, p. 378] "gesture space," a division of concentric squares of the space around a person performing gestures while seated (see Figure 2, right) with three main regions—*center*, *periphery*, and *extreme periphery*,[2]—and seventeen subregions.[3] From the *center* to the *extreme periphery*, gesture articulation requires more space and, implicitly, more physical effort.
- Gesture-Type. We classified the input type implemented by the *on-body* and *on-wheelchair* gestures into five categories: *pointing* (the hand points to a specific body part or a part of the wheelchair, without touching it), *tap* (a quick touch on the body or the wheelchair, usually performed in less than one second), *touch* (a touch longer than a tap), *grasp* (the hand firmly grasps a body part or a part of the wheelchair), and *stroke* (the hand swipes on a surface, draws a symbol, mimics controlling a continuous slider, etc.). The last four categories were inspired by Bergström and Hornbæk's [9, p. 77:3] taxonomy of on-skin input, to which we added *pointing* due to the ubiquity of deictic gestures. This set of five categories is convenient to position a variety of *on-body* and *on-wheelchair* gestures on a continuum ranging from non-contact (*pointing*) to contact-based gestures, where the latter are differentiated by the duration and type of contact. For *in-air* gestures, we used three categories: *pointing* and *stroke*, defined as above, and *hand pose* (i.e., the hand adopts a symbolic pose, such as "thumbs-up").
- Handedness, adopted from McNeill [61], specifies the hand(s) involved in gesture articulation: *left hand (LH)*, *right hand (RH)*, *two same hands (2SH)*, and *two different hands (2DH)*.[4]

[2] For reasons of coding simplicity, we considered McNeill's [61] "center-center" included in the "center" region.
[3] Center and eight subregions for periphery and extreme periphery; see Figure 2, right.
[4] Terminology and abbreviations used by McNeill [61, p. 379] for gesture coding, which we adopt for consistency purposes.

Table 2: The list of referents used in our end-user gesture elicitation study.

	Referent	Description provided to the participants	References†
Actions			
1.	Place call	Open the phone application to place a call	[72]
2.	Answer call	Answer an incoming phone call	[26,40,72]
3.	Send text	Open the messaging application to send a text message	[14,37]
4.	Send email	Open the email application to send an email	[66]
5.	Turn on/off lights	Turn on/off the lights (lights turn on if they are off and vice versa)	[26,41]
6.	Turn on/off the TV	Turn on/off the TV (the TV turns on if it is off and vice versa)	[22,26,41]
7.	Emergency call	Call the emergency contact from the phone application	[40]
Content			
8.	Photo/video	Get direct access to photos/videos; the first photo is displayed on a screen	[14,41,74]
9.	Music	Get direct access to music; the first file starts playing	[14,74]
10.	Email	Get direct access to email; the most recent email is displayed on a screen	[14,41,74]
11.	Contacts	Get direct access to phone contacts, which are displayed on a screen	[72]
12.	E-book	Get direct access to e-books; the last accessed book is displayed on a screen	[14,74]
13.	Agenda/calendar	Get direct access to the agenda/calendar, displayed on a screen	[74]
14.	Social media	Get direct access to the most recent social media notifications, displayed on a screen	[14,22,57,74]
Navigation			
15.	Next horizontal	Go to the next element in a list, e.g., show the next photo or go to the next TV channel	[22,26,37,40,41,50,57,69, 72,96,104]
16.	Previous horizontal	Go to the previous element in a list	same as for ref. 15
17.	Next vertical	Move up in hierarchy, e.g., go to the top-level menu, or increase the value of a parameter, e.g., audio volume, light intensity, etc.	[26,37,40,41,57,66,72, 104]
18.	Previous vertical	Move down in hierarchy or decrease the value of a parameter	same as for ref. 17
19.	Undo	Cancel or reverse the effect of the most recently executed command	[37,40,69,96]
20.	Menu	Open the menu of the current application, e.g., show the TV menu	[37,40,66,69,96]
21.	Home screen	Go to the home screen of the current application	[50,57,66,72]

†Papers from the scientific literature on gesture elicitation, from which we selected our referents, included: the top-10 most influential gesture elicitation studies, according to [91, p. 860], elicitation studies with people with motor impairments [22,57,104], an elicitation study focused on content type [74], content categories used during the chairables study [14], and gesture elicitation studies for wearables [26,40].

The last two categories specify bimanual gestures, where the hands may adopt the same or different poses and movements.

These measures were extracted independently by two researchers, who confronted their results. The average Gwet's [28] AC1 coefficient[5] was .816 (SD=.107) with a cumulative membership probability of 100%, indicating a substantial level of consensus according to the Landoch-Koch benchmarking scale. Differences were discussed and, when consensus could not be reached (2.6% of the cases), were settled by majority vote with the intervention of a third researcher.

3.4.2 Agreement between elicited gestures. We evaluated the agreement between participants' gestures with AR_ϵ, a measure computed automatically from the gesture descriptions following the "computer" model of agreement analysis [90]:

$$\text{AR}_\epsilon(R) = \frac{\sum_p \sum_{q \neq p} [\delta(p,q) \le \epsilon]}{N(N-1)} \cdot 100\% \quad (1)$$

where N is the number of gesture proposals elicited for referent R, δ is the dissimilarity function used to compare gestures p and q, ϵ is a positive value representing the tolerance at or below which two gesture descriptions are sufficiently similar to be considered equivalent, and $[\cdot]$ is Kronecker's function that evaluates to 1 when the inner expression is true and 0 when false. With this definition, AR_ϵ takes values between 0% (no agreement) and 100% (all the gestures are equivalent). To evaluate the dissimilarity δ between two gestures p and q, we used their descriptions with the five measures of gesture articulation, Gesture-Locale, Gesture-Locale-Detail, Gesture-Extent, Gesture-Type, and Handedness, described in Subsection 3.4.1. Thus, any gesture p was represented as p=(p_1, p_2, p_3, p_4, p_5), where p_1 specifies the gesture locale and p_5 the hands configuration, e.g., p may be (*on-body*, *left ear*, *upper periphery*, *touch*, *RH*). Since these variables are categorical, we implemented δ with the probabilistic information theoretic approach proposed by Lin [52], one of the best performing distances for categorical data [11], also employed by Vatavu and Wobbrock [90]:

$$\delta(p,q) = 1 - \sum_{k=1}^{5} w_k S_k(p_k, q_k) \quad (2)$$

where $S_k(p_k, q_k)$ is the per-attribute similarity between any two values of the k-th categorical attribute, and w_k is the weight assigned to the k-th attribute, as follows:

$$S_k(p_k,q_k) = \begin{cases} 2log\left(\pi_k(p_k)\right) & p_k = q_k \\ 2log(\pi_k(p_k) + \pi_k(q_k)) & \text{otherwise} \end{cases} \quad (3)$$

$$w_k = \frac{1}{\sum_{k=1}^{d} log(\pi_k(p_k)) + log(\pi_k(q_k))} \quad (4)$$

$\pi_k(x)$ is the sample probability of the k-th attribute to take value x, which we estimated from our collected data, e.g., π_1(*on-body*)=.476, π_2(*left ear*)=.026, π_3(*upper periphery*)=.216, π_4(*touch*)=.342, and $\pi_5(2DH)$=.078 for the previous example; see Section 4 that presents these results for the corresponding measures. According to Eq. 3,

[5]AC1 is a more stable coefficient of agreement than Cohen's κ; see [28]. We used the irrCAC R package to compute AC1.

Lin's [52] measure assigns higher weights to matches on frequent values and lower weights to mismatches on infrequent values [11].

3.4.3 Gesture ratings. We evaluated participants' perceptions about their own gestures using 7-point Likert scales:

- GESTURE-EASE, adapted from Wobbrock *et al.* [96], measures the perceived ease of gesture articulation with a rating from 1 ("very difficult") to 7 ("very easy").
- GESTURE-GOODNESS, adapted from Wobbrock *et al.* [96], measures the goodness of fit between the proposed gesture and the corresponding referent with a rating from 1 ("not fit at all") to 7 ("very good fit").
- RECALL-EASE, adapted from Zaiţi *et al.* [103], measures user perception of the recall likeliness of the proposed gesture with a rating from 1 ("very difficult") to 7 ("very easy").
- SOCIAL-ACCEPTABILITY, adapted from Rico and Brewster [71], measures participants' willingness to perform the proposed gestures in public with a rating from 1 ("unwilling at all") to 7 ("very willing").

3.5 Statistical Analysis

We employ non-parametric Friedman and Wilcoxon signed-ranked tests to analyze the effect of REFERENT and REFERENT-CATEGORY on participants' gesture ratings. We aggregate the repeated measurements extracted from the videos and use Wilcoxon tests to compare observed percentages against expected ones (e.g., 33.3% chances to observe an *on-body*, *in-air*, or *on-wheelchair* gesture). To examine the effect of REFERENT and REFERENT-CATEGORY on the repeated measurements collected for the categorical variables, such as GESTURE-EXTENT and GESTURE-TYPE, we fit generalized linear mixed-effects models with the Poisson distribution and Powell's BOBYQA optimizer [7]. Finally, we use growth rates r and dissimilarity-consensus logistic modeling [85] to analyze the relationship between AR_ϵ and ϵ.

4 RESULTS

We report results about our participants' preferences and perceptions of *on-body*, *in-air*, and *on-wheelchair* input from an analysis of 231 gestures elicited in response to 21 referents.

4.1 Gesture Locale and Extent

We found that about one in two gestures (47.6%) was performed on or with reference to the body, 40.7% were in air, and 11.7% on or with reference to the wheelchair. The observed percentages of *on-body* and *on-wheelchair* gestures were significantly different from chance (V=48.5, p=.036 and V=3.0, p=.011) with *on-body* gestures being significantly more common (p=.007, Bonferroni corrections applied at α=.05/3=.0167); see Figure 2, top left. A GLMM analysis revealed a statistically significant effect of REFERENT-CATEGORY on GESTURE-LOCALE ($\chi^2_{(2)}$=6.069, p=.048), but not of REFERENT ($\chi^2_{(20)}$=15.823, p=.728, *n.s.*). We found more *on-body* gestures (62.3%) for accessing *Content*, e.g., 72.7% of the gestures elicited for "social media," and more *in-air* gestures (61.0%) for *Navigation*, e.g., 81.8% of the gestures elicited for "next vertical" and "previous vertical"; see Figure 2, top right. The percentages of *on-wheelchair* gestures were roughly similar, between 10.4% and 13.0%, across REFERENT-CATEGORY.

The specific locations where the gestures were performed are illustrated in Figure 2, bottom left. *On-body* gestures were performed mostly with reference to the head (16.0%), followed by arms (12.2%), legs (10.4%), and torso (4.7%), and 4.3% involved multiple body parts, e.g., touching both the left and right thighs. *In-air* gestures were performed in front of the body (29.4%), and only very few on the left (2.2%) and right (1.3%) sides. The most common *on-wheelchair* gestures involved touching the armrests (6.1%). Furthermore, Figure 2, bottom right shows the distribution of the GESTURE-EXTENT categories in McNeill's [61] gesture space. A percentage of 27.7% of the gestures were performed in the *center* and only 11.2% in the *extreme periphery*, while the upper part of the *periphery* region contained 21.6% of the elicited gestures due to their reference to the head. Combined, gestures performed in the *center* and the upper subregions of the *periphery* and *extreme periphery* around the head represented more than half (56.2%) of the elicited gestures.

4.2 Gesture Type

We found a larger preference for *touch* (34.2%) and *hand pose* (22.5%) compared to *tap* (14.3%), *stroke* (14.3%), *pointing* (12.1%), and *grasp* (2.6%) gestures; see Figure 3, top. A GLMM analysis revealed a significant effect of REFERENT-CATEGORY on GESTURE-TYPE ($\chi^2_{(2)}$=8.887, p=.01), but not of REFERENT ($\chi^2_{(20)}$=20.865, p=.405, *n.s.*). Referents from the *Navigation* category that had spatial connotations received *pointing* and *stroke* gestures in response, e.g., 54.5% of the gestures elicited for "next vertical," 45.5% for "previous vertical," and 45.5% for "undo." *Touch* gestures were predominant for the referents of the *Content* category, e.g., 63.6% of the gestures elicited for "agenda/-calendar," "contacts," "music," and "social media." The distribution of gesture types was mainly split between *touch* and *hand pose* for the *Actions* referents, e.g., 63.6% *hand pose* gestures to "place a call" and 36.4% *touch* gestures to "send a text message," respectively.

4.3 Handedness

The large majority (78.3%) of the elicited gestures involved one hand, and were significantly more common ($Z=-2.497$, p=.013) than two-hand gestures (18.6%); see Figure 3, bottom. On rare occasions (3.0%), a few participants proposed head gestures,[6] which we exceptionally allowed since they were considered the best fit to the corresponding referents. Although gestures performed with the right hand were more common than those performed with the left (46.3% and 32.0%), the percentages were not significantly different from expected chance (p>.05) with no significant difference either between the two categories ($Z=-.801$, p=.423, *n.s.*). Of the bimanual gestures, 11.3% were symmetric (*2SH*, V=6.0, p=.017) and 7.4% involved different movements and poses (*2DH*, V=1.0, p=.004).

4.4 Agreement Rates

We computed agreement rates AR_ϵ for each REFERENT using the procedure described in Subsection 3.4.2. We used the tolerance level ϵ=0 to specify that two gestures are equivalent if and only if they have the same GESTURE-LOCALE, GESTURE-LOCALE-DETAIL, GESTURE-EXTENT, GESTURE-TYPE, and HANDEDNESS attributes. Out

[6]The seven head gestures (7/231=3.0%) observed in our study included turning the head left (P_{10}), up (a gesture that P_8 proposed for two referents), down (P_8), and back (P_8), eyes wide open (P_9), and taking a deep breath (P_6), respectively.

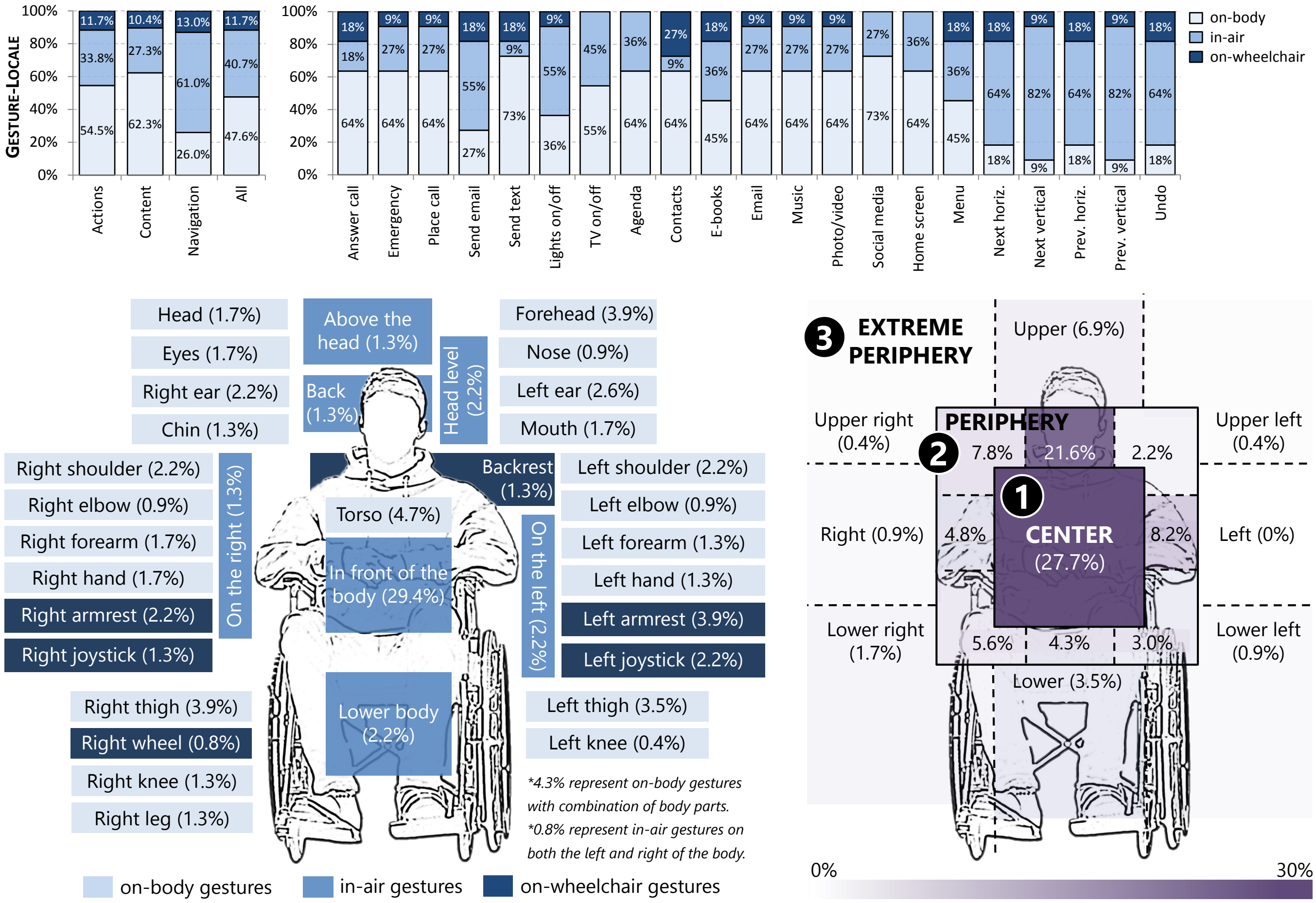


Figure 2: Distribution of Gesture-Locale per Referent-Category and Referent (top), Gesture-Locale-Detail (bottom left), and Gesture-Extent (bottom right). Note the high preference for *on-body* and *in-air* gestures.

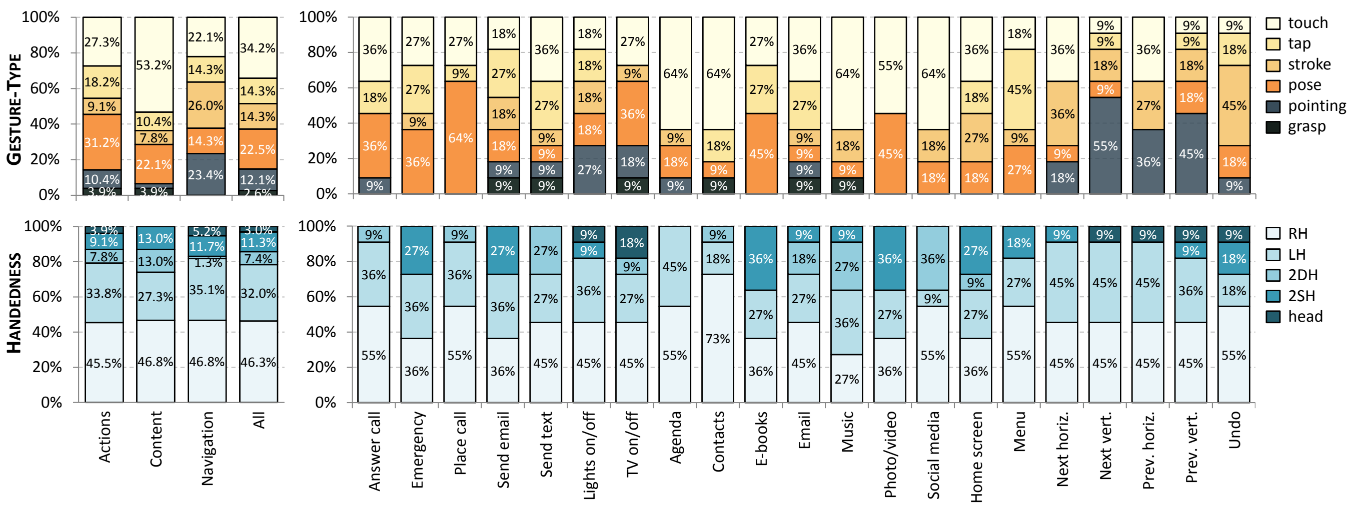


Figure 3: Distribution of Gesture-Type (top) and Handedness (bottom) per Referent-Category and Referent. Note the high preference for *touch* and *hand pose* gestures (top) and *unimanual* gestures (bottom), respectively.

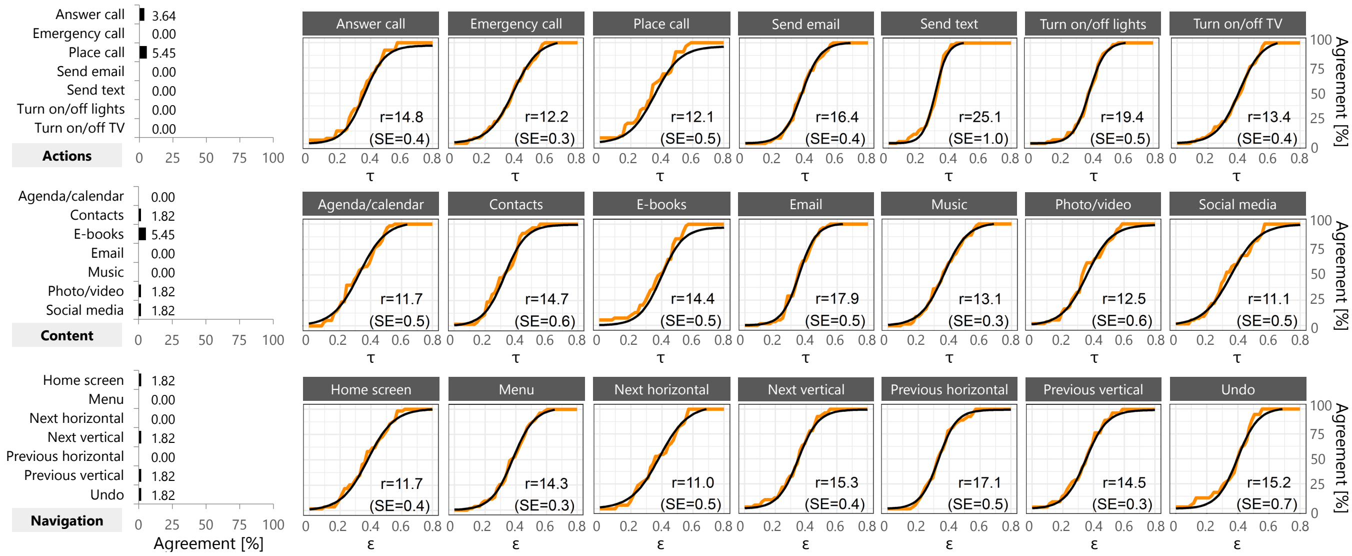


Figure 4: Agreement rates [90] (left) and growth-rate dissimilarity-consensus curves [85] (right). Note the low agreement ($AR_\epsilon \leq$5.5%) and little variation in growth rates (M=14.7, IQR=3.1). Actual δ data is shown in orange, logistic models in black.

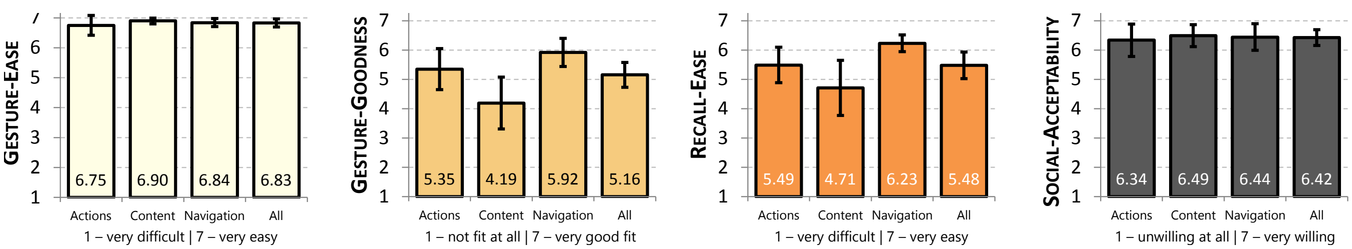


Figure 5: Participants' ratings of the gestures they proposed to effect various referents (higher values denote better ratings).

of the total number of (11·10)/2=55 pairs of gestures for each Referent, we found between 0 and 3 pairs in agreement (Mdn=0, M=0.71, SD=0.95) and, correspondingly, very low agreement rates, between 0.0% and 5.5% (M=1.3%, SD=1.7%); see Figure 4, left.

According to these results, no consensus gesture set can be established for any of the referents because of our participants' different preferences for gestures or, perhaps, our too restrictive gesture equivalence criteria. To rule out the latter, we recomputed the agreement rates AR_ϵ without considering the influence of some of the gesture attributes, but the consensus did not increase significantly: M=2.0% (SD=2.1%) without Handedness (i.e., we considered two gestures equivalent regardless of the hand used to perform them), M=3.6% (SD=2.7%) without Handedness and Gesture-Locale-Detail (i.e., we considered two gestures equivalent regardless of the hand used to perform them and the specific details of their articulation on the body, wheelchair, or in air), and M=4.7% (SD=4.6%) without Handedness and Gesture-Extent (i.e., we considered two gestures equivalent regardless of the hand used to perform them and the region in space where they were performed). This analysis revealed that the lack of consensus was determined by participants' different preferences for gestures. To further confirm this finding, and also to learn more about agreement formation for the elicited gestures, we employed the dissimilarity-consensus method [85], an approach to agreement analysis designed to be agnostic to the criterion ϵ. Following this method, we performed logistic modeling of the growth curves of AR_ϵ function of ϵ. The estimated values for the C_0 and C_∞ coefficients of the logistic models were close to zero (M=0.75, SD=0.60) and 100 (M=100.3, SD=1.93), respectively, and the growth rates r were statistically significant (p<.001), indicating a good fit of the logistic models for our data; see [85, p. 8] for goodness of fit criteria in dissimilarity-consensus analysis. Figure 4, right shows growth rates r that vary little (M=14.7, SD=3.3, IQR=15.3-12.2=3.1) between the referents. The similar speeds at which the agreement rates computed for different referents increase with increasingly larger tolerance values ϵ indicate similar processes of agreement formation for those referents. Thus, the diversity observed in the elicited gestures must have another cause than the mere difference between the conditions of the Referent variable, an aspect that we examine in detail in Subsection 4.6 in relation to our participants' self-reported motor impairments.

4.5 User Perception of the Elicited Gestures

Figure 5 shows the mean ratings of Gesture-Ease, Recall-Ease, Gesture-Goodness, and Social-Acceptability for the gestures proposed by our participants. We found statistically significant effects of Referent-Category on Recall-Ease ($\chi^2_{(2)}$=8.512, p=.014) and Gesture-Goodness ($\chi^2_{(2)}$=7.818, p=.020), complemented by significant effects of Referent ($\chi^2_{(20)}$=50.240 and $\chi^2_{(20)}$=56.961, p<.001), but not on Gesture-Ease and Social-Acceptability (p>.05, *n.s.*). Post-hoc Wilcoxon signed-rank tests (Benjamini & Hochber FDR corrections applied) revealed statistically significant differences between the *Content* and *Navigation* categories for Recall-Ease (p=.043), and between *Content* and *Actions* (p=.035) and *Content* and *Navigation* (p=.035) for Gesture-Goodness. Overall, our participants evaluated their own gestures easy to articulate (M=6.83/7), easy to recall (M=5.48/7), a good fit to the referents (M=5.16/7), and socially acceptable (M=6.42/7). Despite the little agreement between users' gesture proposals (see Subsection 4.4), we found high gesture ratings within users, which suggests a design approach based on personalized gesture sets.

4.6 Relationship Between Motor Impairments and Gesture Characteristics

We computed visualizations of the relationship between the articulation characteristics of the elicited gestures and participants' self-reported motor impairments; see Figure 6. In this figure, each participant is represented on one row and the columns correspond to the measures of gesture articulation from Subsection 3.4.1—Gesture-Locale, Gesture-Locale-Detail, Gesture-Type, Handedness, and Gesture-Extent,—which we have used consistently throughout our analysis, including for computing agreement rates. In total, seven circular layout charts are presented for each participant to show the correspondence between the participant's motor impairments and the characteristics of their gesture articulations.

For example, P_1 reported slow movements (Mo), poor coordination (Co), fatigue (Fa), and difficulty controlling distance (Dis); see the first row of Table 1 and the first row of Figure 6, respectively. During gesture elicitation, P_1 proposed *on-body* (76.2%) and *in-air* (23.8%), but not *on-wheelchair* (0.0%) gestures. The first circular chart puts into correspondence P_1's preferences for Gesture-Locale (shown at the bottom part of the layout) with their self-reported motor impairments (at the top of the layout) using ribbons with a color coding matching that used to represent Gesture-Locale in Figure 2. The next three circular charts show P_1's preferences for locations, according to the Gesture-Locale-Detail categories, where P_1 performed *on-body*, *in-air*, and *on-wheelchair* gestures. (Since P_1 did not propose *on-wheelchair* gestures, the corresponding chart is empty for this category.) The rest of the charts have the same structure (motor impairments at the top and gesture characteristics at the bottom) and follow the color codings used for Gesture-Type (yellow and orange, correspondence with Figure 3, top), Handedness (cyan hues, correspondence with Figure 3, bottom), and Gesture-Extent (magenta, correspondence with Figure 2, bottom right). Thicker ribbons denote a higher percentage of a given gesture characteristic, e.g., P_1 performed 76.2% *on-body* gestures (first chart), 47.6% *touch* gestures (fifth chart), and 61.9% of the gestures in the *periphery* region (last chart).

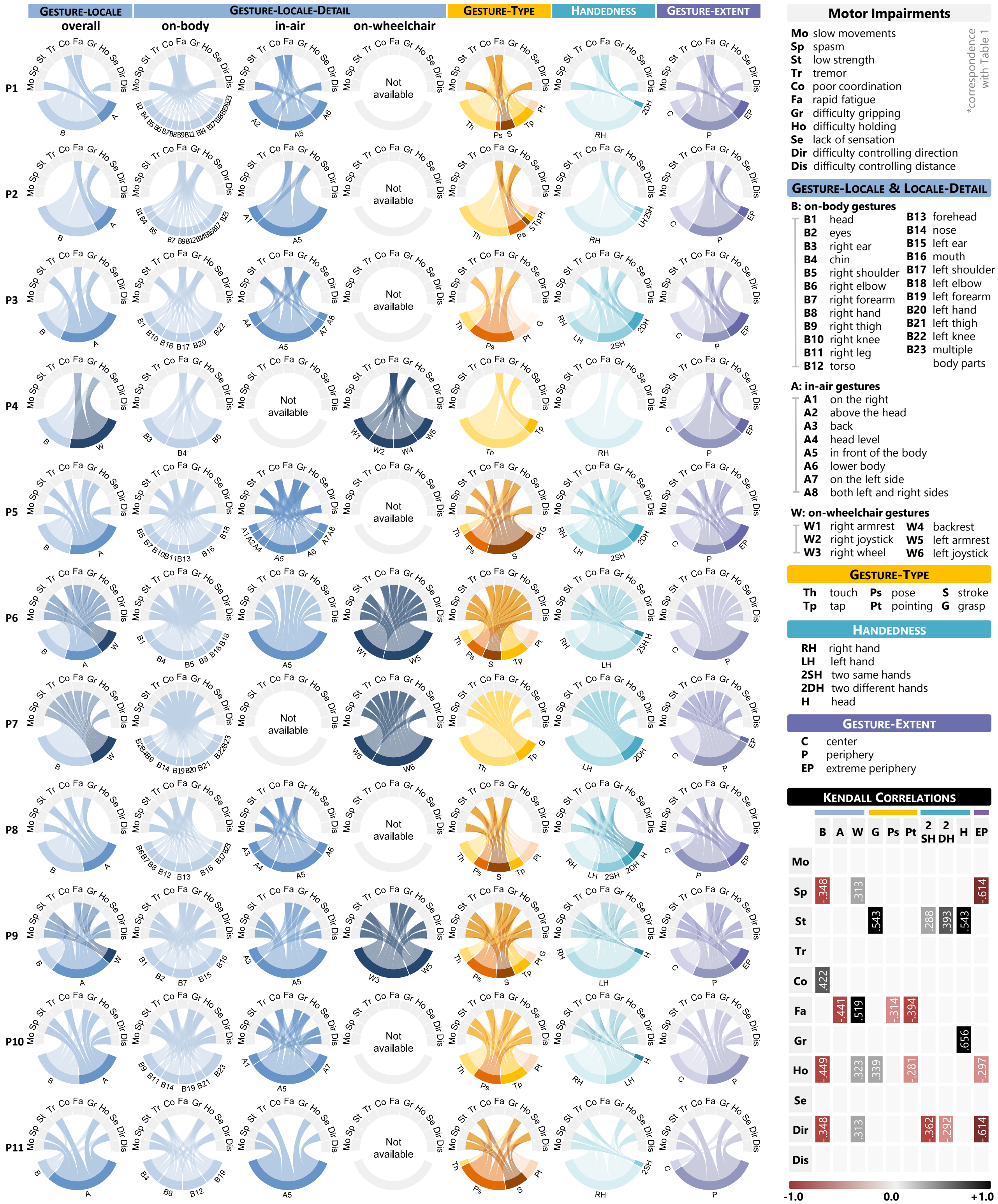
Several interesting observations are revealed by the correspondences illustrated in Figure 6, for which we found support in the magnitudes of Kendall's τ_b coefficients[7] computed between the gesture articulation measures, e.g., Gesture-Locale or Handedness, and the eleven categories of self-reported motor impairments listed in Table 1, e.g., low strength (St), which we treated as binary variables in this analysis (1 indicates the presence and 0 the absence of a specific motor impairment for a given participant). Figure 6, bottom right shows an overview of Kendall's τ_b coefficients for the correspondences that we identified between the characteristics of the elicited gestures and our participants' motor impairments. These correspondences are discussed in detail next.

4.6.1 Gesture locale. *On-wheelchair* gestures were proposed by four participants only (P_4, P_6, P_7, and P_9), all of which reporting the combination of rapid fatigue (Fa, $\tau_{b(11)}$=.519) and difficulty holding (Ho, $\tau_{b(11)}$=.323). We also found medium associations between the observed percentage of *on-wheelchair* gestures and the difficulty to control the direction of movement (Dir, $\tau_{b(11)}$=.313) and spasm (Sp, $\tau_{b(11)}$=.313), two motor symptoms shared by P_6, P_7, and P_9. These three participants also reported the largest numbers of motor impairments (10, 8, and 8, respectively, see Table 1) and preferred gestures supported by the wheelchair armrests. *On-body* gestures were proposed by all the participants but in different percentages, from 14.3% (P_{11}) to 76.2% (P_1). They were generally favored by the absence of spasm (Sp, $\tau_{b(11)}=-.348$), difficulty controlling direction (Dir, $\tau_{b(11)}=-.348$), and difficulty holding (Ho, $\tau_{b(11)}=-.449$), and were preferred to other gesture types when poor coordination (Co, $\tau_{b(11)}$=.422) was present. Finally, *in-air* gestures were not proposed at all by P_4 and P_7, who both reported rapid fatigue (Fa), a symptom negatively associated ($\tau_{b(11)}=-.441$) with the percentage of observed *in-air* gestures. In the case of P_4, fatigue was accompanied by uneven development of the arms caused by Osteogenesis Imperfecta, a health condition in which bones fracture easily. Figure 1, right from Section 1 shows an overview of all participants' preferences of Gesture-Locale.

4.6.2 Gesture extent. All of the participants proposed gestures in the *center* (27.7%) and *periphery* (57.6%) regions. Gestures in the *extreme periphery* were rare (14.7%), and three participants (P_6, P_{10}, and P_{11}) did not use them at all; see Figure 6, last column. These participants shared a combination of three motor symptoms, for which we found medium and strong negative associations with the percentage of *extreme periphery* gestures: spasm (Sp, $\tau_{b(11)}=-.614$), difficulty holding (Ho, $\tau_{b(11)}=-.297$), and difficulty controlling the direction of movement (Dir, $\tau_{b(11)}=-.614$), respectively.

4.6.3 Gesture type. All of the participants proposed *touch* gestures to a fairly large extent and most participants (8/11) also used *taps*, the longer version of a *touch*, according to our Gesture-Type categories. Also, almost all of the participants used *pointing*, except for P_4 and P_7 (Figure 6, fifth column), who reported rapid fatigue (Fa) and difficulty holding (Ho), two motor symptoms that associated negatively with the percentage of *pointing* gestures ($\tau_{b(11)}=-.394$ and $\tau_{b(11)}=-.281$). These two participants were also the only ones

[7] Kendall's τ [38] measures the ordinal association between two quantities and is preferable to other measures based on concordant and discordant pairs; see [1, p. 191]. The τ_b variant [39] is adjusted for ties. According to https://www.spss-tutorials.com/kendalls-tau/#kendalls-tau-interpretation, a value of .21 indicates a "medium" association and .35 a "strong" one. We report only τ_b coefficients that are above the "medium" threshold.



	B	A	W	G	Ps	Pt	2SH	2DH	H	EP
Mo										
Sp	-.348		.313							-.614
St				.543			.288	.393	.543	
Tr										
Co	.422									
Fa		-.441	.519		-.314	-.394				
Gr									.656	
Ho	-.449		.323	.339		-.281				-.297
Se										
Dir	-.348		.313				-.362	-.292		-.614
Dis										

Figure 6: Relationship between participants' self-reported motor impairments and their gesture articulation characteristics; see also Table 1 and Figures 2 and 3. The bottom right table summarizes Kendall's τ_b coefficients for the trends discussed in the text.

that did not propose *hand poses*, for which we found a negative association with rapid fatigue (Fa, $\tau_{b(11)}$=− .314). The four participants that used *grasps* (P_3, P_5, P_7, and P_9) shared the low strength (St, $\tau_{b(11)}$=.543) and difficulty holding (Ho, $\tau_{b(11)}$=.339) motor symptoms. *Stroke* gestures were also popular, being proposed by more than half of the participants (7/11), of which P_5 stood out with 52.4% of the gestures he proposed to invoke the referents from our study.

4.6.4 Handedness. Unimanual gestures (78.4%) were more common than bimanual gestures (18.6%). All of the participants proposed unimanual gestures, and the use of either the left or right hand was determined by their specific motor conditions. For example, P_7's right hand was almost paralyzed, so she performed most of the gestures with the left hand (71.4%), while the rest (28.6%) were bimanual. P_1, P_4, and P_{11} performed gestures with the right hand exclusively because of the left hand being paralyzed (P_1), less developed than the right hand (P_4), or affected more by Parkinson's symptoms (P_{11}). For most of the participants (7/11), the percentage of their bimanual gestures was well below 10% (M=3.4%), but three participants (P_3, P_5, and P_8) stood out with a high preference for bimanual gestures (57.1%, 57.1%, and 38.1%, respectively). Figure 6, sixth column shows that these participants shared a distinct combination of motor symptoms, for which we detected medium to strong associations with the percentage of observed bimanual gestures: absence of the difficulty to control the direction of movement (Dir, $\tau_{b(11)}$=− .362 for *2SH* and $\tau_{b(11)}$=− .292 for *2DH*) and symptoms of low strength (St, $\tau_{b(11)}$=.288 for *2SH* and $\tau_{b(11)}$=.393 for *2DH*). Head gestures, proposed by P_6, P_8, P_9, and P_{10}, who considered them more appropriate to effect specific referents compared to gestures of the hand (see Figure 6, sixth column) and, thus, were exceptionally accepted in our study (3.0%), associated positively with the presence of low strength (St, $\tau_{b(11)}$=.543) and difficulty gripping (Gr, $\tau_{b(11)}$=.656) motor symptoms, respectively.

4.6.5 Summary. Our analysis revealed that the gestures proposed by different participants were different in terms of the combination of Gesture-Locale, Gesture-Locale-Detail, Gesture-Extent, Gesture-Type, and Handedness characteristics. Instead of a consensus gesture set that would be representative for a large group of users—a common end result for gesture elicitation studies [90,96]—we found highly individualized gesture preferences. Since this result could not be attributed solely to differences between referents (see our dissimilarity-consensus analysis from Subsection 4.4), we analyzed it in the context of our participants' specific motor impairments and identified several correspondences. Next, we adopt the lenses of ability-based design [94,95]—an approach to designing interactive systems where designers focus on users' abilities, not disabilities, and systems change to match and adapt to those abilities—to propose implications for accessible *on-body*, *in-air*, and *on-wheelchair* gesture input for wheelchair users.

5 ABILITY-BASED DESIGN OF ACCESSIBLE ON-BODY, IN-AIR, AND ON-WHEELCHAIR GESTURE INPUT

Our results revealed that *both* user preference *and* motor impairments influence the characteristics of gesture articulations. Next, we capitalize on Gesture-Locale, Gesture-Locale-Detail, Gesture-Type, Gesture-Extent, and Handedness to outline practical implications for accessible gesture input for wheelchair users with the seven principles of ability-based design [94,95]: *ability, accountability, availability, adaptability, transparency, performance,* and *context.*

According to the *ability* principle [94], designers should focus on users' abilities, not disabilities. We suggest:

❶ **Design gesture sets that are customizable in terms of gesture locale, i.e., *on-body, in-air, on-wheelchair,*** according to the motor ability of the user to raise the arms, rotate the wrists, and form specific hand poses for *in-air* gestures, reach to specific body parts for *on-body* gestures, and extend and bend fingers to touch the armrest for *on-wheelchair* gestures, respectively. *Example:* P_7 proposed *on-body* and *on-wheelchair* touch, tap, and grasp gestures (see Figure 6), which involved a stable physical target to support the hand and finger, but not *in-air* gestures because of her Parkinson's condition causing spasm and tremor.

❷ **For a given locale, design gestures that are customizable in terms of how the locale is implemented.** *Example:* not all of the participants proposed *in-air* gestures and, from those who did (9/11), only less than half could raise their arm to the head or above the head, two regions for which they assigned specific meanings; see the conditions A2 and A4 of the *in-air* gesture locale in Figure 6, third column. However, all of the participants performed gestures in front of the body (A5 in Figure 6). *Example:* because of his specific condition of Osteogenesis Imperfecta, P_4 has small legs and short stature. However, unlike all of the other participants, who performed *on-body* gestures no lower than the thigh level, he was able to touch his legs and feet without any difficulty.

The *accountability* principle [94] states that designers change systems, not users to foster usability. We propose:

❸ **Use gesture recognizers that are invariant to the body part articulating the gesture.** *Example:* participant P_7's right hand was almost paralyzed, so she performed the large majority of the gestures with her left hand. Unlike conventional touchscreens that are agnostic to the finger, hand, or body part implementing touch input, an aspect that favors diverse coping strategies for people with upper-body motor impairments to use mobile devices effectively [3,34], detecting *in-air* gestures may require computer vision approaches, e.g., using a video camera placed above the wheelchair armrest [42], on the user's head [46], or in the environment [100]. Since such systems can easily distinguish various body parts [75], their flexibility should not diminish, but foster usability, e.g., designers should not expect a gesture to always be performed with the left hand or always be unimanual.

According to the *availability* principle [94], designers use affordable and available software and hardware. As wheelchairs become smart devices [49] with embedded sensors, actuators, and communications (see Subsection 2.1), these resources can be exploited to detect and recognize a diversity of gesture input. Moreover, the sensors integrated in users' mobile and wearable devices could be employed for the same purpose. Our practical implication is:

❹ **Reuse embedded sensors from smart wheelchairs, mobile devices, and wearables to detect a variety of *on-body*, *in-air*, and *on-wheelchair* gestures.** *Example: in-air* and *on-body* gestures can be detected with conventional video cameras from smartphones, tablets, and smartwatches [54,77]. *Example:* accelerometers and gyroscopes, common in off-the-shelf wearables, such as smartwatches, fitness trackers, and armbands, can detect gestures performed *in-air*, *on-body*, and with objects; see [17,47,88]. *Example:* NFC/RFID technology has been used for body-centric interactions [102] and interactions with objects, including the wheelchair [56].

The *adaptability* principle [94] states that interfaces provide the best possible match to users' abilities. We propose:

❺ **Design gesture sets of *on-body*, *in-air*, and *on-wheelchair* gestures that can be used interchangeably in the personal and peripersonal space.** *Example:* a directional swipe gesture can equally be performed in mid-air [69], drawn on the palm [29], or sketched on the wheelchair armrest [13]. *Example:* some motor abilities are invariably lost as the result of health conditions increasing in severity, e.g., Parkinson's is a neurodegenerative brain disorder with symptoms that begin gradually and worsen over time. Participant P_7 (Parkinson's diagnostic for 13 years) proposed *on-body* and *on-wheelchair* touch, tap, and grasp gestures (see Figure 6, fifth column) involving a stable physical target to support the hands, but not *in-air* gestures because of her condition causing spasm and tremor. However, P_{11} (Parkinson's diagnostic for 8 years) proposed *in-air* gestures in front of the body.

Interfaces that implement the *transparency* principle [94] give users awareness of their adaptive behavior. Our practical implementation of this principle is as follows:

❻ **Accompany gesture articulation with feedback matching gesture locale.** While *on-body* and *on-wheelchair* gestures are naturally accompanied by the haptic sensation of feeling touching the intended target, e.g., the palm of the other hand or the wheelchair armrest, *in-air* gestures are not, which makes non-contact gestures more challenging to produce by users [24] and recognize by computers [80]. *Example:* when *in-air* gestures are implemented with wearables [88], vibrotactile feedback impacts positively user experience [44]. *Example:* lack of sensation in a body part involved in the articulation of an *on-body* gesture, e.g., on the supporting palm, could be compensated with an accessible feedback modality to confirm reaching the target. P_6 reported lack of sensation below the upper arms, caused by spinal cord injury at vertebrae C4-C5, yet he proposed *on-body* gestures on the head, chin, mouth, shoulder, elbow, and right hand. Independent of gesture locale, providing feedback about gesture sensing and recognition [36] or feedforward during gesture articulation [20] can increase usability and provide users with the means to inspect, discard, or revert, if needed, the outcome of a command.

The *performance* principle [94] states that systems employ data collected about their users to provide the best possible match to the users' abilities. We propose the following implication:

❼ **Model the user's gesture preferences.** *Example:* predilection for specific gesture locales (e.g., *on-body*, *on-wheelchair* instead of *in-air* for P_7), specific gesture types (e.g., *touch* and *tap*, but not *pointing*, *grasp*, or *stroke* for P_4), handedness (e.g., exclusive use of the right hand by P_1, P_4, and P_{11} for unimanual gestures), but also body parts (e.g., P_6 proposed head instead of hand gestures, when they believed that head gestures were better suited to a specific referent) are examples of information that an adaptive gesture recognizer [12,92] could use to tune its training set and/or parameters.

According to the *context* principle [94], systems use context to anticipate and accommodate effects on users' abilities:

❽ **Complement and enrich smartphone-based interaction with *on-body*, *in-air*, and *on-wheelchair* gestures.** *Example:* some wheelchair users prefer keeping their smartphones always available, e.g., on the wheelchair armrest or their lap and thigh [67,87]. This context favors conjunct use of the smartphone and gesture input performed in the vicinity of the smartphone in the personal and peripersonal space of the user. The result is higher flexibility for users to select the gesture modality best suited to their abilities in context: gross movements of the large muscle groups for *on-body* and *in-air* gestures vs. fine-precision aiming and tapping abilities for touch input on the smartphone and *on-wheelchair* armrest, respectively. Another opportunity is new interaction techniques for the wheelchair space, e.g., a combined gesture that starts with the user touching the smartphone and continues with pointing to the TV to transfer content in the style of AirLink [16] interactions. Conjoint use of smartphone-based input and gestures performed in the personal and peripersonal space of the wheelchair user for various interactive contexts and systems, e.g., public interactive displays [89], is an interesting direction to explore in future work.

❾ **Enable easy switching between gesture locales and types.** *Example:* infer the context, e.g., indoor, outdoor, private, public, interlocutors, type of audience, etc., to enable switching to gesture locales and gesture types socially acceptable in that context, e.g., from potentially attention seeking [30] or conspicuous [71] *on-body* and *in-air* gestures to more subtle and discreet *on-wheelchair* gestures performed on the joystick or armrest.

6 LIMITATIONS AND FUTURE WORK

There are several limitations to our experiment, which we present in this section together with ways to address them in future work.

Our sample of participants was of N=11 wheelchair users only, which is just over half the size of the most common choice (N=20) for the number of participants in gesture elicitation studies, according to statistical findings from Villarreal *et al.* [91]. In this general context, our sample size falls in the [10,20) interval alongside 38% of more than two hundred published gesture elicitation studies, but is larger than the sample size from other 11% studies that used less than ten participants; see [91, p. 859]. However, in the specific context of elicitation studies involving people with motor impairments, our sample size is identical to that of Malu *et al.* [57], who elicited accessible smartwatch interactions. In the same context of accessibility research, our sample size is also representative of those from studies traditionally published at CHI and ASSETS, according to Mack *et al.*'s [55, p. 8] findings that revealed a median number of N=10 participants with motor or physical disabilities. Nevertheless, a larger sample size can offer more opportunities for gesture analysis, e.g., by relating participants' preferences for *on-body*, *in-air*, and *on-wheelchair* gestures to other motor and physical disabilities not present in our sample, such as arthritis or lost limbs. Also, a larger, multicultural sample of participants would enable understanding potential interactions between motor symptoms and cultural factors given that gestures develop culturally, a fact that has implications for the design of gesture user interfaces [21,60]. Thus, we recommend more investigations in future work with a larger sample of participants to examine aspects such as these and, potentially, reveal more practical implications for accessible computing. To foster such future work, including replications [33] of our findings as well as extension and repurposing [27] of the data collected in our experiment toward new discoveries, we release our gesture dataset and results obtained with our gesture articulation measures freely available to download from the web address http://www.eed.usv.ro/~vatavu.

Another limitation of our experiment is that we did not record participants' gestures in a computational form, which would have enabled further insights on their gesture articulations with specialized measures and tools, e.g., [4,86], or evaluating gesture recognizers. We recommend such examinations in future work to increase our understanding of both user and system performance with gestures of various types performed from the wheelchair space.

7 CONCLUSION

We examined the articulation characteristics of *on-body*, *in-air*, and *on-wheelchair* gestures proposed by wheelchair users for common actions, types of digital content, and navigation commands in interactive systems, for which we employed a diversified set of measures of gesture articulation, user perception, and agreement analysis. Our results revealed a high preference for *on-body* and *in-air* compared to *on-wheelchair* gestures, having specific articulation characteristics according to the users' specific motor abilities. Based on our findings, we proposed practical implications, structured using the principles of ability-based design, for gesture input performed from the wheelchair in the user's personal and peripersonal space. We look forward to more examinations of *on-body*, *in-air*, and *on-wheelchair* gesture input, reflective of both users' preferences and motor abilities, toward more accessible gesture-based interactions performed from the space of the wheelchair.

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