Understanding Gesture Input Articulation with Upper-Body Wearables for Users with Upper-Body Motor Impairments

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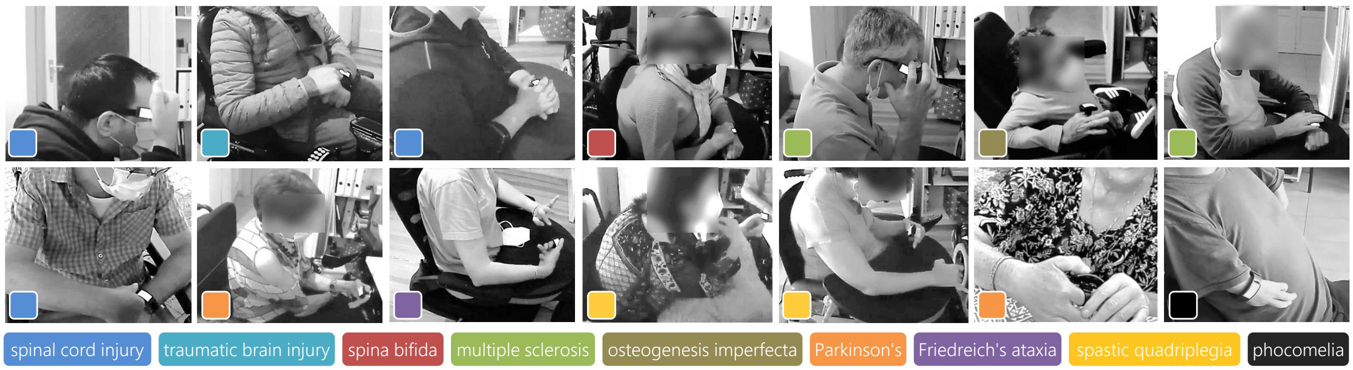

Figure 1: Users with upper-body motor impairments articulating touchscreen *stroke-gestures* and mid-air *motion-gestures* on and with a wearable. The device is worn on the wrist (as a watch), on the index finger (as a ring), and on the head (attached to the temple of a pair of glasses). Different colors in this figure indicate different motor impairment conditions and causes.

ABSTRACT

We examine touchscreen *stroke-gestures* and mid-air *motion-gestures* articulated by users with upper-body motor impairments with devices worn on the *wrist*, *finger*, and *head*. We analyze users' gesture input performance in terms of production time, articulation consistency, and kinematic measures, and contrast the performance of users with upper-body motor impairments with that of a control group of users without impairments. Our results, from two datasets of 7,290 stroke-gestures and 3,809 motion-gestures collected from 28 participants, reveal that users with upper-body motor impairments take twice as much time to produce stroke-gestures on wearable touchscreens compared to users without impairments, but articulate motion-gestures equally fast and with similar acceleration. We interpret our findings in the context of ability-based design and propose ten implications for accessible gesture input with upper-body wearables for users with upper-body motor impairments.

CCS CONCEPTS

• **Human-centered computing → Accessibility technologies.**

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KEYWORDS

Motor impairments, smartwatches, smartglasses, smart rings, gesture input, accessible input, wearables.

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1 INTRODUCTION

Wearables are surpassing smartphones as today's fastest-growing technological innovation for mobile users [13,69]. Some wearables, such as fitness trackers and smartwatches, have already become mainstream with one-in-five Americans using them on a regular basis [98]. Others, such as NFC rings for POS payments and smartglasses for AR/VR, represent growing markets [33,84]. In this context, designing wearable interactions, such as interactions based on touch [63,65] and motion [36,59,108] gestures, that are effective [46], intuitive [30], socially acceptable [72], and comfortable [51] is paramount for the successful adoption of wearables.

However, gesture-based interactions with off-the-shelf wearables are based on certain assumptions about users' motor abilities, reflected in the form factors and intended uses of these devices. For instance, a swipe on a smartwatch [63] assumes the ability to move the hand towards the watch, land a finger on the watch, move the finger steadily to produce a straight, uninterrupted path on the touchscreen, and lift off the finger to finalize input. A ring gesture [30] assumes the motor ability to move the wearing finger, rotate the wrist, make a hand pose, and possibly raise the forearm as well. A head gesture [108] assumes the ability to use the cervical muscles to rotate and tilt the head. Upper-body motor impairments cause challenges in producing gesture input with wearables implementing such assumptions; see Figure 1 for various finger, hand, and body poses adopted by users with motor impairments while performing gestures on devices worn on the finger, wrist, and head. Thus, designing gesture interactions that match diverse motor abilities is key to making wearables more accessible.

Unfortunately, few works have examined gesture input for devices worn on the upper body and users with upper-body motor impairments to understand the impact of such assumptions on users' input performance. Most of this prior work has focused on documenting accessibility challenges for off-the-shelf fitness trackers, smartwatches, and smartglasses [16,66,68,70], while only a few studies have quantified numerically users' gesture input performance by reporting preference ratings [63,65], task completion times and error rates [64], and Fitts' law evaluations [65] for these devices. Although this prior work has contributed useful findings about how people with upper-body motor impairments use gestures with off-the-shelf wearables and recent work has started exploring new promising wearables designed for the upper body that feature new types of gesture input, such as teeth [85], facial [34], and eye gaze [111] gestures, there is still little research available on this topic,[1] which limits our understanding of gesture input performance with wearables under various motor abilities. Moreover, the gesture types that have been examined in the scientific literature for wearable interactions are simple, mostly taps and directional swipes, while for some commercially available wearables, such as smart rings, gesture input performance has not been examined at all for users with upper-body motor impairments; see Şiean and Vatavu's [21] literature review on accessible wearable interactions.

In this paper, we contribute new empirical results about gestures articulated by users with upper-body motor impairments by considering (i) multiple locations for placing a wearable on the upper part of the body, (ii) a large palette of gesture types, and (iii) a variety of corresponding assumptions to perform those gestures. Specifically, we focus on *stroke-gestures* (i.e., gesture paths articulated on touchscreens [80,91,104], such as drawing letter "S" on a smartwatch) and *motion-gestures* (i.e., movements of a body part in mid-air [30,59,108], such as a clockwise rotation of the finger wearing a smart ring). These two input modalities encompass many gesture types that involve both large and small muscle groups as well as gross and fine motor skills of the fingers, hands, and arms. Thus, they address a diversity of assumptions about users' motor abilities. In this context, our practical contributions are as follows:

(1) We present results from an experiment with 28 participants, of which 14 with upper-body motor impairments, that evaluated the articulation characteristics of *stroke-gestures* produced on a small touchscreen worn as a *watch*, as a *ring*, and on the temple of a pair of *glasses*. We report, from a large dataset of 7,290 gestures, that users with upper-body motor impairments produce stroke-gestures that are two times slower, 36% less consistent, and with 39% more strokes as the same gesture types produced by users without impairments.
(2) We present results from a second dataset of 3,809 *motion-gestures* articulated with the *wrist*, *finger*, and *head*. Unlike for stroke-gestures, we found no significant differences in production times between motion-gestures articulated by users with and without upper-body motor impairments. Moreover, we found similar acceleration and jerk characteristics of the motion-gestures produced by the two user groups.
(3) Based on our empirical results, we use the principles of ability-based design [101] to discuss ten implications for accessible gesture input for users with upper-body motor impairments and wearables for the finger, wrist, and head.

[1] A recent scientific literature review on wearable interactions for users with motor impairments [21] identified only four papers on smartwatch input, five papers on smartglasses, and one position paper about smart rings.

2 RELATED WORK

We examine in this work stroke-gestures and motion-gestures articulated by users with upper-body motor impairments with rings, watches, and glasses. Thus, we relate primarily to prior work on gesture input for such devices in Subsections 2.1 and 2.2, and discuss accessible wearable interactions in Subsection 2.3.

2.1 Stroke-Gesture Input with Wearables

Research on stroke-gesture input for wearables has addressed topics from prototyping new devices [11,32,87] to gesture recognition techniques [87,106], analyses of users' preferences for gesture input [24,30], and investigations of application opportunities [1,31,41,44,109]. For example, TouchRing [87] is a finger-worn input device that leverages a capacitive sensor to enable touch and swipe gestures on the surface of a ring. Ringteraction [32] is an interaction technique for coordinated thumb-index input on a ring integrating a small display and capacitive sensors. The Swipeboard [19] and SwipeZone [37] techniques for eyes-free input on ultra-small touchscreens leverage users' spatial memory of the QWERTY keyboard for text entry on smartwatches and smartglasses with 19.58 and 8.73 words-per-minute, respectively. Regarding users' preferences for intuitive gestures for wearables, Gheran *et al.* [30] conducted a gesture elicitation study [103] for smart rings and reported that 16.4% of the 672 gestures proposed by their participants were performed on the ring surface as button presses, touches, and stroke-gestures. Also, a recent systematic literature review on ring input [94] analyzed a number of 954 ring gestures found in academic publications, of which 30.6% were taps and touch input on the ring and 26.2% were swipes and stroke-gestures on a supporting surface, including the ring.

Besides dedicated gesture recognition and interaction techniques developed for the unique sensing capabilities of various wearables, touchscreens and touchpads integrated in watches and glasses enable stroke-gesture input that can be recognized with established recognizers, such as the "$-family." For example, $1 [104] is a unistroke gesture recognizer, $N [5] extends $1 to multistrokes, and $P [91] enables articulation-independent stroke-gesture recognition. Moreover, several tools exist for evaluating user performance with stroke-gesture input in terms of gesture articulation consistency [4] and relative accuracy [92,93].

2.2 Motion-Gesture Input with Wearables

The scientific literature on motion-gesture input with wearables is equally rich in terms of gesture recognition algorithms [59,60,106], interaction techniques [20,35,107], and applications [35,36,41]. For example, WRIST [110] is a gesture sensing and interaction technique that employs IMU readings from a smartwatch and a smart ring to exploit the relative orientation difference of the two devices. Wen *et al.* [99] presented "Serendipity," a technique for recognizing fine-motor finger gestures with off-the-shelf smartwatches, Xu *et al.* [107] demonstrated finger-writing on surfaces with hand movements detected by the smartwatch, and Liu *et al.* [59] elicited movements of the fingers and wrist to understand the potential of wrist-worn recognition with an IMU-only recognizer *vs.* a low-cost wrist-flex sensor. WristWhirl [36] enables wrist gestures in the form of directional marks and free-form shapes for one-handed continuous input on smartwatches; in WrisText [35], users enter text on smartwatches by whirling the wrist to point to letters arranged on a circular keyboard; Cioată and Vatavu [20] explored interactive opportunities for two watches worn on both hands; and RotoSwype [38] was designed for word-gesture typing by leveraging the orientation of a smart ring.

Several tools exist to assist the design of motion-gestures. For instance, MAGIC (Multiple Action Gesture Interface Creation) [7] enables gesture creation, recognition testing, and identification of false positives; GDATK (Gesture Dimensionality Analysis Toolkit) [90] evaluates dissimilarity measures for motion-gestures and reports recognition rates and execution times for gesture sets with various sampling rates and bit depths; and GestMAN (GESTure MANagement) [62] is a cloud-based tool designed to assist with the acquisition and management of gesture sets.

2.3 Accessible Wearable Interactions for Users with Motor Impairments

Despite the rich literature on gesture input for wearables, research on accessible gesture-based interactions for users with motor impairments has been scarce. A recent systematic literature review on this topic [21] identified just a handful of papers addressing smartwatches, smartglasses, and head-mounted displays (HMDs), while most of the prior work has largely focused on applications, such as navigation assisted by AR glasses for wheelchair users [2], providing assistance during everyday activities [68], control of assistive robots with head gestures and eye gaze input [39], and enabling immersive VR experiences with HMDs [26].

A few studies have documented accessibility challenges for wearables [63,65,70] and proposed design recommendations and more accessible input techniques. For example, after examining the accessibility of Google Glass, Malu *et al.* [65] proposed an alternative input technique involving touchpads affixed to the body or wheelchair. Mott *et al.* [70] conducted semi-structured interviews with people with limited mobility to understand their experience with VR, and reported barriers regarding the physical accessibility of VR devices, such as putting on and taking off HMDs, adjusting the HMD head strap, or maintaining view of the controllers. They also documented preferences for alternative input methods for HMDs, such as voice and gaze input instead of less accessible motion controllers. Malu *et al.* [63] evaluated the accessibility of existing smartwatch gestures (taps, swipes, and scribbling letters for text input) with ten users with upper-body motor impairments, and reported several challenges regarding button, swipe, and tap-based interactions, e.g., some of their participants found edge swipes to be the most difficult types of directional stroke-gestures. The authors also elicited gesture alternatives involving the touchscreen, bezel, and wristband for sixteen common smartwatch actions. Of the total number of 528 gestures created by users with upper-body motor impairments, 69% involved interactions with the index, middle, or little fingers, and there was a majority preference for unistrokes. In a follow-up study, Malu *et al.* [64] compared touchscreen and bezel watch gestures, and reported a speed-accuracy tradeoff: the touchscreen was faster, but the bezel more accurate. The study also revealed that participants largely favored the touchscreen, which felt more comfortable and easy to use despite the higher error rate.

Designing accessible computing for wheelchair users has been equally addressed in terms of studies to understand accessibility challenges [16,66], but also to inform the design of new input devices [17,18,65]. For instance, Carrington *et al.* [18] introduced "chairables," i.e., devices designed to work within the workspace of the wheelchair that are either worn on the body or mounted on the wheelchair frame that, among several input modalities, also enable gesture input. An example is GestRest [17], a chairable input device for the armrest featuring a pressure-sensitive surface that enables touch, flick, and pressure-based gestures.

Gesture input for other wearables has been examined to a less extent for people with motor impairments: Gheran *et al.* [29] discussed in a position paper potential applications of smart rings as assistive devices; Pedrosa *et al.* [74] and Rajanna [77] examined foot-operated wearables for text entry; and Fu and Ho [28] and Postolache *et al.* [75] developed applications for data gloves. A few works have explored new forms of gesture-based input, implemented with various body parts, for interaction with mobile and wearable devices. For example, Fan *et al.* [25] explored gestures performed with eyelids for navigating mobile applications, and introduced an interaction language of eyes opening and closing, e.g., a "double blink" gesture is the sequence eyelids closing, opening, and closing again. Goel *et al.* [34] described a wireless, non-intrusive and non-contact X-band Doppler system for detecting facial gestures, such as touching the tongue against the cheek, puffing the cheeks, and moving the jaws. Sun *et al.* [85] explored teeth gestures, such as different ways to tap with the teeth, useful for various content navigation and control tasks, e.g., a discreet teeth tap can be used to reject a phone call during a socially inconvenient situation, while a "holding" tap with delayed release provides continuous input for adjusting audio volume. We refer readers to Şiean and Vatavu's [21] survey of accessible wearable interactions for users with motor impairments.

In this context, more scientific investigations are needed to understand how users with upper-body motor impairments articulate gestures on wearable devices of various kinds in order to consolidate and advance the current knowledge in the community regarding the design of accessible wearable interactions. In the next section, we present our experiment designed to collect and analyze a variety of stroke-gestures and motion-gestures performed with devices worn on the upper body.

Table 1: Demographic details about the participants with upper-body motor impairments, their self-reported impairments using the categories from [27], WHODAS 2.0 health and disability scores [105], and task completion rates for our experiment.

Participant	Health condition†	Since	Self-reported impairments‡											WHODAS	Stroke-gestures CR§			Motion gestures CR§		
			Mo	Sp	St	Tr	Co	Fa	Gr	Ho	Se	Dir	Dis	2.0 score	Watch	Ring	Glasses	Watch	Ring	Glasses
P_1 (41 yrs., male)	Spinal cord injury (C4-C5)	2003	–	✓	✓	–	–	✓	✓	✓	✓	✓	✓	52.1	100%	–	100%	100%	–	100%
P_2 (44 yrs., male)	Traumatic brain injury	1996	✓	–	–	–	✓	✓	–	–	–	–	✓	45.8	100%	100%	100%	–	100%	100%
P_3 (57 yrs., male)	Spinal cord injury (T7)	2013	–	–	–	–	–	✓	–	✓	–	–	–	41.7	100%	100%	100%	100%	100%	100%
P_4 (47 yrs., female)	Spina bifida	1974	–	–	✓	–	–	✓	–	✓	–	–	–	39.6	100%	100%	100%	95.8%	100%	100%
P_5 (48 yrs., male)	Multiple sclerosis	1987	✓	–	✓	–	✓	✓	–	✓	–	–	–	52.1	100%	97.9%	100%	97.9%	100%	100%
P_6 (48 yrs., male)	Osteogenesis imperfecta	1973	–	–	–	–	–	✓	–	✓	–	–	–	33.3	–	100%	100%	–	100%	100%
P_7 (49 yrs., male)	Multiple sclerosis	1999	✓	–	✓	–	✓	–	✓	✓	–	–	✓	39.6	100%	100%	–	100%	100%	100%
P_8 (65 yrs., male)	Spinal cord injury (C4-C5)	2011	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	✓	37.5	100%	–	–	100%	–	100%
P_9 (53 yrs., female)	Parkinson's disease	2008	–	✓	✓	✓	✓	✓	✓	✓	–	✓	–	37.5	–	99.0%	–	100%	100%	41.7%
P_{10} (43 yrs., female)	Friedreich's ataxia	2013	✓	–	✓	–	✓	–	✓	–	–	–	–	14.6	99.0%	100%	100%	100%	100%	100%
P_{11} (47 yrs., female)	Spastic quadriplegia	1974	✓	✓	✓	–	–	✓	✓	✓	–	✓	✓	37.5	100%	99.0%	100%	100%	100%	100%
P_{12} (46 yrs., female)	Spastic quadriplegia	1975	–	✓	✓	–	✓	–	✓	✓	–	✓	✓	33.3	100%	100%	100%	100%	100%	100%
P_{13} (57 yrs., female)	Parkinson's disease	2013	✓	✓	–	✓	–	–	–	✓	–	✓	–	12.5	99.0%	100%	100%	100%	100%	100%
P_{14} (27 yrs., male)	Phocomelia	1994	–	–	–	–	–	–	✓	–	–	–	–	16.7	100%	–	100%	100%	100%	100%
		Summary	**7**	**6**	**9**	**2**	**7**	**9**	**8**	**11**	**2**	**6**	**6**	**35.3**	**85.6%**	**78.3%**	**78.6%**	**85.3%**	**85.7%**	**95.8%**

†The code in the parentheses denotes the affected vertebra(e), e.g., "(C4)" refers to traumatic injury at the 4th cervical vertebra.

‡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.

§Completion Rate (CR) of the experiment, e.g., if a participant performed only 34 of the 12 (gestures) × 8 (repetitions) = 96 stroke-gesture trials for *watch*, then CR=34/96=35.4%.

3 EXPERIMENT

We conducted a gesture collection experiment to understand the performance of people with upper-body motor impairments with gesture input articulated on and with devices worn on the wrist (as a watch), finger (as a ring), and head (as glasses).

3.1 Participants

A number of 14 people with upper-body motor impairments (8 male and 6 female), aged 27 to 65 years (M=48.0, SD=8.8), participated in our experiment. They were recruited via a non-profit organization providing technical assistance to people with disabilities. Participants' scores on the WHODAS 2.0 test—a generic instrument from WHO for standardized measurement of health and disability across cultures [105]—varied between 12.5 and 52.1 (M=35.3, SD=12.6) on a scale of 100.[2] Other demographic details are presented in Table 1. We used convenience sampling to recruit a control group of 14 people without impairments: 11 male and 3 female with an age range of 21 to 67 years (M=32.9, SD=12.0) similar to that of the motor impairments group. In total, 28 people took part in our experiment. Except for one person with motor impairments, all of the participants were smartphone users. Four participants (14.3%), of which one with motor impairments, were also using smartwatches.

3.2 Design

Our experiment design was mixed with three independent variables:

(1) MotorImpairment, nominal variable with two conditions: *with* and *without* upper-body motor impairments, administered between subjects.
(2) Wearable, nominal variable with three conditions: *watch*, *ring*, and *glasses*, representing devices worn on the *wrist*, *finger*, and *head*, administrated within subjects.
(3) Modality, nominal variable with two conditions: *stroke-gestures* performed on the device and *motion-gestures* of the body part wearing the device, administered within subjects.

The two Modality conditions require distinct motor abilities to touch and draw on a small surface and to move a body part in mid-air, respectively. In combination with the conditions of Wearable, the motor abilities are further differentiated. Thus, we designed gesture sets for each combination of Wearable and Modality; see Subsection 3.4. Although the individual gestures from these sets, e.g., "circle" or "swipe left," specify the conditions of a fourth variable, Gesture, we do not consider the effect of specific gestures in our analysis, but instead see the gestures as a sample drawn from all possible gesture types, and we perform data aggregation on this variable.[3] However, we do refer to individual gestures in Section 6 to provide applied information to practitioners regarding gesture set design for accessible input on wearable devices.

3.3 Apparatus

We used the Samsung Gear Fit 2 smartwatch[4] (1GHz Exynos 3250 Dual Core CPU, 512MB RAM, Wi-Fi), for which we developed a custom Tizen Web application[5] to collect stroke-gestures with the integrated touchscreen (216×432 pixel resolution, 322ppi) and motion-gestures with the built-in 3-axis accelerometer in the *watch* condition. To ensure that gestures were collected with the same sensing resolution across all of the Wearable conditions, we repurposed the Gear Fit 2 device for the *glasses* and *ring* conditions as well. To this end, we detached the watch from its strap and affixed it with a 3D-printed support to the temple of a pair of glasses and to a 3D-printed ring, respectively; see Figure 2. The small size of Gear Fit 2 (17mm × 34mm) and its small weight (30g) made it suitable for these other two conditions from several alternatives of touchscreen devices that we considered for our experiment.

[2]According to the normative data report of Andrews *et al.* [3] 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.

[3]The Gesture variable would be treated as a random effect in mixed effects models [67].

[4]https://www.samsung.com/us/mobile/wearables/smart-fitness-bands/samsung-gear-fit2-large-black-sm-r3600daaxar

[5]https://docs.tizen.org/application/web/index

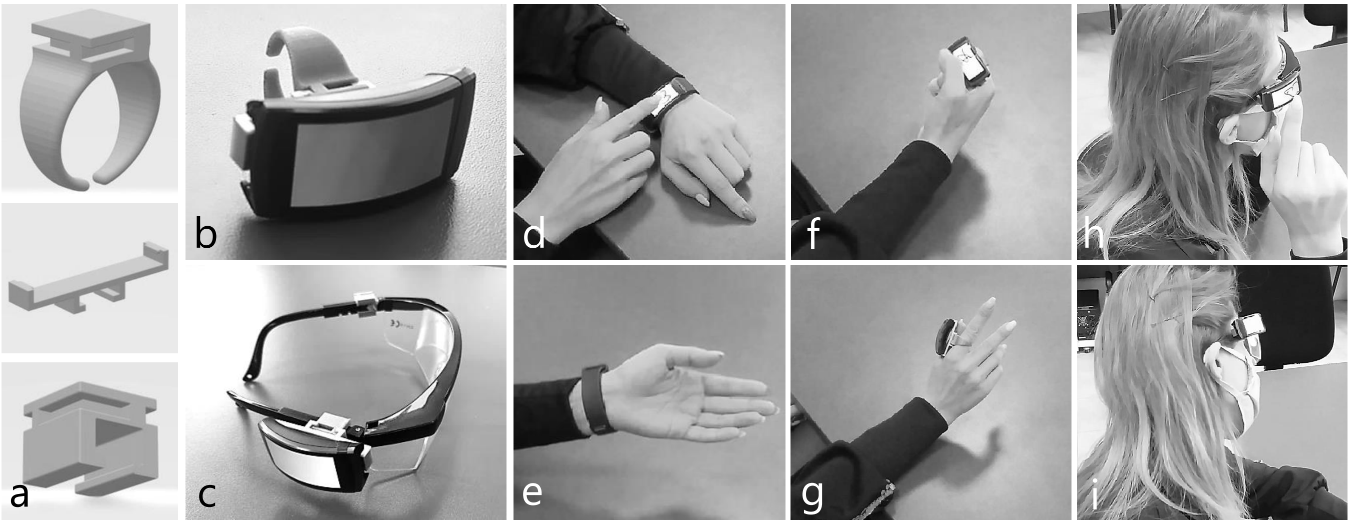

Figure 2: Apparatus used during the experiment. The Samsung Gear Fit 2 device was worn on the wrist, finger, and head using 3D-printed hooks (a-c). Stroke-gestures were produced with the opposite hand in the watch condition (d), the thumb of the same hand in the ring condition (f), and with the hand on the same side of the body for glasses (h). Motion-gestures were produced with movements of the arm and wrist (e), finger (g), and head (i), respectively.

3.4 Gesture Sets

We designed a set of stroke-gestures for touchscreen input in the *watch*, *ring*, and *glasses* conditions, and three sets of motion-gestures involving movements of the *wrist*, *finger*, and *head*.

3.4.1 Stroke-gesture set. Stroke-gestures are paths produced on a touchscreen, for which symbolic associations are created with system functions, e.g., letter "S" for "Save." We designed a set of twelve stroke-gestures (Figure 3, top) by considering the following attributes to ensure a diversity of gesture types in our experiment:

- *Number of strokes.* A stroke is a continuous movement of the finger on the touchscreen between two finger-down and finger-up events. For instance, a swipe is produced in one stroke, but drawing letter "X" requires two strokes. Multistroke gestures, for which the finger lifts off of the screen to land at a different location, are more demanding in terms of motor difficulty than unistrokes. Our set contains eight unistrokes (66.7%) and four multistrokes (33.3%); see Figure 3, top and the Sk symbol in the legend.
- *Shape complexity.* We used Isokoski's [45] definition of shape complexity[6] to include in our set gestures of various complexities, from 1 (directional swipes) to 6 (the "six-point star"); see legend SC in Figure 3, top.
- *Execution difficulty.* We employed Vatavu *et al.*'s [97] ranking rule to evaluate perceived execution difficulty based on production time,[7] which we estimated using GATO [55], a prediction tool for stroke-gestures. The DR legend in Figure 3, top shows the ranking of the twelve gestures from the easiest (1) to the most difficult (12) to execute.
- We included *letters* and *common shapes* and *symbols* in our set due to their ubiquity in stroke-gesture UIs, such as in the "augmented letters" [80] or "gesture search" [58] techniques.

3.4.2 Motion-gesture set. Motion-gestures are movements of a body part, such as rotating the wrist or tilting the head. We designed three gesture sets for the *finger*, *wrist*, and *head* corresponding to the three conditions of Wearable independent variable:

(1) For the *ring* condition, we drew inspiration from Gheran *et al.*'s [30] elicitation study of ring gestures, Liu *et al.*'s [59] elicitation study of finger gestures, and Vatavu and Bilius' [94] GestuRING library.[8] The motion-gestures are shown in Figure 3, bottom-left, characterized according to the *complexity*[9] and *locale*[10] (C L) dimensions of Gheran *et al.* [30].

(2) Gestures for the *wrist* in the *watch* condition were inspired from Shimon *et al.*'s [6] elicitation study of non-touchscreen watch gestures, Liu *et al.*'s [59] elicitation of wrist gestures, the WristWhirl [36] and WrisText [35] techniques for one-handed input with smartwatches, wrist rotation gestures for shortcuts [12], and the WearOS watch gestures.[11] Figure 3, bottom-middle illustrates the *wrist* gestures from our set characterized along the *complexity*,[12] *duration*,[13] and *size*[14] dimensions of Shimon *et al.*'s [6] taxonomy (C, D, and S).

[6]The minimum number of lines to represent the shape to still be recognizable by a human observer [45], e.g., the complexity of letter "A" is 3.
[7]Gesture A is likely to be perceived more difficult to produce than gesture B if the production time of A is greater than that of B [97].

[8]Available from http://www.eed.usv.ro/~vatavu/projects/GestuRING.
[9]*Simple* or *compound:* simple gestures have meaning on their own, while compound gestures can be decomposed into individually meaningful gestures [30].
[10]The location where the gesture is performed. We adopt the *on surface* and *in mid-air* categories from [30] and introduce the *on other finger* category.
[11]https://support.google.com/wearos/answer/6312406?hl=en.
[12]Hand gestures can be *simple* or *compound* [6].
[13]*Short* (less than 0.5s) *medium* (between 0.5s and 1.5s), and *long* (more than 1.5s) [6].
[14]Three categories: *small* (the gesture can be performed in less than 439cm^3 of physical space), *medium* (between 439cm^3 and 1467$cm^3$5), and *large* (over 1467cm^3) [6]. Shimon *et al.* exemplify air taps as small, twists of the wrist as medium, and rotational motions along multiple joints as large gestures, respectively (p. 3826).

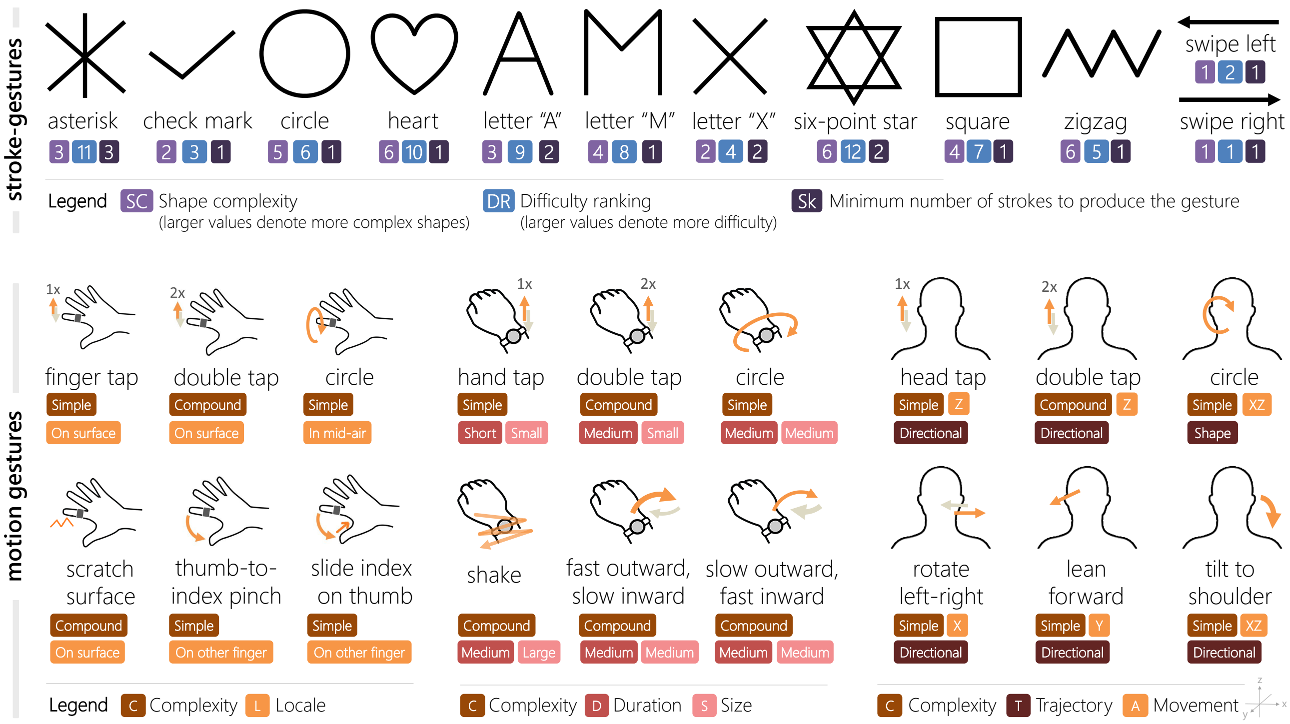

Figure 3: The sets of stroke-gestures (top) and motion-gestures (bottom) used in our experiment, 30 gesture types in total.

(3) Head gestures for the *glasses* condition were inspired from Yan *et al.*'s [108] head gesture space for HMDs, Vanderdonckt *et al.*'s [89] elicitation study of head gestures, the Headbang [43] and HeadTurn [73] interaction techniques, and prior work on head gesture input for controlling the power wheelchair for people with motor impairments [47]. Figure 3, bottom-right shows these gestures characterized along the *complexity*,[15] *trajectory*,[16] and *movement*[17] dimensions (C, T, and A) from Vanderdonckt *et al.*'s [89] and Yan *et al.*'s [108] taxonomies.

3.5 Task

A custom software application, running on a laptop, displayed the gesture representing the current trial. Gestures were presented both visually (as in Figure 3) and with a short text description, e.g., "square" or "lean forward." The order of gesture types was randomized for each combination of Wearable × Modality. After each trial, the gesture collected by the wearable was sent to the laptop application via Wi-Fi. For stroke-gestures, our application logged x, y, and *touch id* data with timestamps. For motion-gestures, it logged x, y, and z acceleration data with timestamps. Participants were instructed to enter gestures at their normal speed, and had total freedom in terms of the number of strokes, stroke direction, and stroke order for stroke-gestures, and amplitude of movement for motion-gestures. Our only instruction for stroke-gestures was to execute them with the opposite hand in the *watch* condition, the hand on the same side of the body for *glasses*, and with the thumb of the same hand in the *ring* condition. The order of Wearable × Modality was randomized per participant. A training stage took place for each condition with each gesture being performed twice.

[15] Head gestures can be *simple* or *compound*. [89]
[16] Three categories: *directional* (the head moves in different directions), *shape* (the head draws geometrical shapes), and *character* (the head draws characters or numbers) [108].
[17] Translation and rotation along the X, Y, and Z axes; see [108] (p. 198:10).

3.6 Measures

We computed several measures of gesture articulation performance, adopted from prior work on gesture recognition and analysis [4,10, 78,81,92,93,97], which we evaluated as dependent variables in our experiment. Some of the measures are modality specific, e.g., we computed ShapeBending (rad) [4] for stroke-gestures and MeanJerk (m/s^3) [82] for motion-gestures. Other measures apply to both stroke-gestures and motion-gestures, as follows:

(1) TaskCompletionRate represents the percentage of gesture articulation trials completed by a participant, e.g., 95.8% for participant P_4 and motion-gestures performed with the *wrist* in the *watch* condition.
(2) The ProductionTime of a gesture, reported in seconds, represents an instance of the generic task time measure employed in HCI to evaluate user input efficiency [14,54,55,88].
(3) The ArticulationConsistency of a gesture, computed as:

$$\max\left(0, 1 - \frac{\text{average}_h\{\delta(g,h)\}}{\text{average}_{h^*}\{\delta(g,h^*)\}}\right) \quad (1)$$

where g is the gesture for which consistency is computed (e.g., an articulation of an "asterisk"), h represents gestures of the same type (other "asterisks"), and h^* denotes gestures of other types. To compare gestures, we employed Dynamic

Time Warping (DTW)—a dissimilarity function popular for both stroke-gestures and motion-gestures [86,90]—denoted by δ in Eq. 1. ArticulationConsistency computes to 0 when gesture g is more similar to other gesture types than to articulations of the same type (i.e., low consistency) and towards 1 otherwise. Function max() makes sure that the result is always zero for gestures that are highly inconsistent.

While ProductionTime is useful to evaluate the efficiency of gesture input [14,54,55] and ArticulationConsistency provides insights into the variation naturally induced during gesture input [4] with impact on recognition accuracy [4,92], several other measures have been employed in the scientific literature, either for stroke-gesture analysis [56,88,95–97] or recognition [10,49,81] purposes. From these, we selected three commonly used measures to understand the geometric structure (NumStrokes), size (PathLength), and curviness (ShapeBending) of stroke-gesture articulations:

(4) NumStrokes, the number of strokes that constitute a gesture, is a measure of gesture structure that characterizes users' preferences for gesture articulation [4,78,92] or their ability to touch the surface steadily [49,96].
(5) We measured the PathLength of a gesture as the sum of the lengths of the individual strokes, which we computed as the sum of Euclidean distances between consecutive points on the gesture path, as in [78,81,96].
(6) We measured ShapeBending (rad) as the sum of absolute turning angles defined by triples of consecutive points on the gesture path, as in [4,78,78,81,95–97].

For motion-gestures, we selected the following three measures from the scientific literature on gesture analysis [59,82,82]:

(7) MeanAcceleration (m/s^2) is the average magnitude of the composite acceleration as an indicator of the physical effort to produce the gesture. Prior work has used this measure to refer to gesture strength [40] or energy [79].
(8) MeanJerk (m/s^3) is the average magnitude of the composite jerk of the gesture movement, adopted from Ruiz *et al.*'s [82] "Kinematic impulse" category of their taxonomy (p. 202).
(9) NumAxesOfMovement (dimensionless) represents the number of axes on which acceleration is detected, a measure adapted from Ruiz *et al.*'s [82] "Dimension" category of their taxonomy of motion-gestures.[18]

3.7 Statistical Analyses

We employ ANOVA for split-plot designs to analyze the data from our experiment with two independent groups and repeated measures. However, when the normality assumptions are not met (according to Shapiro-Wilk tests) or heteroscedasticity is present in the data (according to Levene's test), we employ a robust statistic procedure described by Wilcox [100] (p. 545) based on 20%-trimmed means.[19] This procedure reports the Q statistic that, like ANOVA, uses the F distribution for the decision rule, but computes Winsorized variances; see Wilcox [100] for advantages of using trimmed means when there are even slight deviations from normality in the data. For multiple comparisons, we use the BWMCP method from Wilcox [100] (p. 610) to control the familywise error rate (FWE).

4 RESULTS: STROKE-GESTURES

We report in this section user performance with stroke-gestures entered on a wearable touchscreen device in the *watch*, *ring*, and *glasses* conditions. We start our analysis with task completion rates.

4.1 Task Completion

We collected a total number of 7,290 gestures from the maximum of 8,064 trials = 3 (conditions of Wearable) × 12 (stroke-gesture types) × 28 (participants) × 8 (repetitions), representing an overall task completion rate of 90.4%. The completion rate was 100% for the participants without impairments and varied between 33.0% and 100% (M=80.8%, SD=25.1%) for the participants with upper-body motor impairments. Participants P_6 (osteogenesis imperfecta) and P_9 (Parkinson's) could not articulate gestures on the *watch* with the opposite hand, P_1 and P_8 (SCI C4-C5) could not move the fingers and wrist and, thus, did not enter gestures in the *ring* condition, and participants P_7 (multiple sclerosis), P_8 (SCI), and P_9 (Parkinson's) had difficulties raising their arms to touch the *glasses*. Table 1 shows the trial completion rate of each participant.

4.2 Gesture Production Time

Production time data deviated from normality for the *watch* and *glasses* conditions and participants without impairments (p<.05 according to Shapiro-Wilk tests) and heteroscedasticity was present (according to Levene's tests, p<.05) and, thus, we used the robust Q test. We found a statistically significant main effect of MotorImpairment on ProductionTime ($Q_{(1,10.037)}$=27.771, p<.001), a significant main effect of Wearable ($Q_{(2,10.499)}$=27.513, p<.001), and a significant interaction between MotorImpairment and Wearable ($Q_{(2,10.499)}$=5.654, p<.05). Overall, participants with upper-body motor impairments performed stroke-gestures two times slower (3.16s *vs.* 1.56s) compared to participants without impairments. Specifically, they took 76% more time to articulate stroke-gestures on the *watch* (2.29s *vs.* 1.30s, p=.011), 125% more time on the *ring* (4.02s *vs.* 1.79s, p=.004), and 105% more time on *glasses* (3.26s *vs.* 1.59s, p=.002); see Figure 4a. Also, participants with upper-body motor impairments produced stroke-gestures that were 43% slower on the *glasses* (p=.018) and 76% slower on the *ring* (p=.004) compared to the same gesture types on the *watch* (FWE for multiple comparisons controlled at α=.05). These results suggest the need for techniques to make gesture input faster for users with upper-body motor impairments, such as gesture abbreviation [9,15], an aspect that we resume in our discussion from Section 6.

4.3 Consistency of Gesture Articulation

ArticulationConsistency data deviated from normality in the *ring* and *watch* conditions (p<.05), hence we used the Q test. We found a significant main effect of MotorImpairment ($Q_{(1,15.152)}$ = 11.119, p<.005), a main effect of Wearable ($Q_{(2,13.271)}$=41.187, p<.001), and a significant interaction between MotorImpairment

[18] Since Ruiz *et al.* [82] were not explicit about how they computed this measure, we counted one axis if the MeanAcceleration for that axis was above 0.1m/s^2, a threshold that we adopted from https://docs.microsoft.com/en-us/windows-hardware/drivers/sensors/accelerometer-thresholds.
[19] Implemented with the bwtrim(...) function from the Rallfun-v38 library, https://dornsife.usc.edu/labs/rwilcox/software.

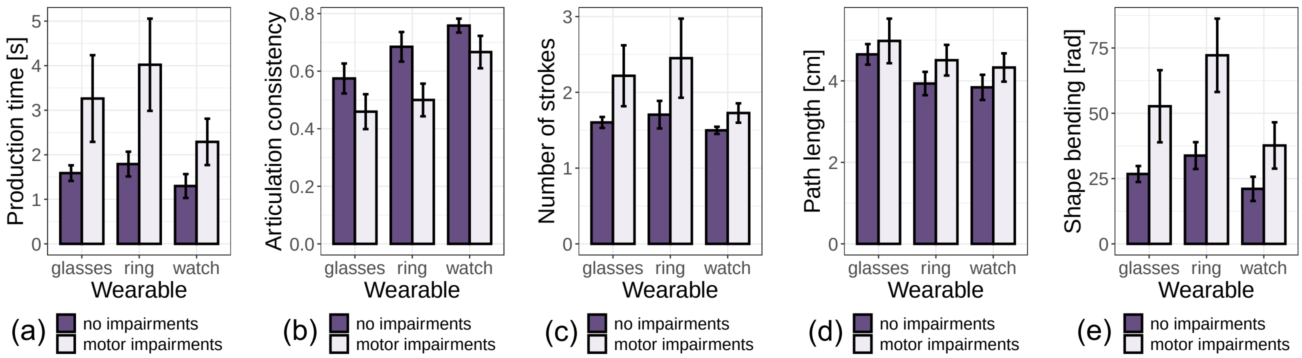

Figure 4: Characteristics of stroke-gestures articulated by participants with and without upper-body motor impairments.

and Wearable ($Q_{(2,13.271)}$=6.112, p<.05). Overall, participants with upper-body motor impairments were less consistent than the participants without impairments (0.55 *vs.* 0.67, 17.9% less consistency) with statistically significant differences found in the *ring* (p=.002) and *watch* (p=.05) conditions; see Figure 4b. ArticulationConsistency increased significantly from *glasses* to *ring* to *watch*, except for the participants with upper-body motor impairments, for which no statistically significant difference was found between *glasses* and *ring* (p=.212, FWE controlled at α=.05). According to Vatavu *et al.* [92], less consistent gestures impact negatively recognition accuracy, unless the recognition approach is tolerant to variations in how stroke-gestures are being articulated [91]. We resume this aspect in Section 6, where we combine ArticulationConsistency and ProductionTime in one single measure of gesture input performance to discuss individual gesture types.

4.4 Geometric Characteristics

We characterize the stroke-gestures produced by our participants with stroke count, length, and shape bending measures.

4.4.1 Number of strokes. Data deviated from normality in four of the six combinations of MotorImpairment × Wearable (p<.05) and heteroscedasticity was present in the *glasses* and *watch* conditions (p<.05). We found a significant main effect of MotorImpairment ($Q_{(1,9.732)}$=7.51, p<.05), a significant main effect of Wearable ($Q_{(2,12.669)}$=16.579, p<.001), and a significant interaction between MotorImpairment and Wearable ($Q_{(2,12.669)}$=7.419, p<.01). Overall, participants with upper-body motor impairments articulated stroke-gestures with a geometric structure having 33% more strokes (2.12 *vs.* 1.60) compared to the same gesture types articulated by the participants without impairments with statistically significant differences for *glasses* (2.22 *vs.* 1.60, p=.004) and *watch* (1.73 *vs.* 1.50, p=.038); see Figure 4c.

4.4.2 Path length. Path length data was normal, but heteroscedasticity was present in the *glasses* condition (p<.05). We found a statistically significant main effect of MotorImpairment ($Q_{(1,17.577)}$ = 12.665, p<.005), a significant effect of Wearable ($Q_{(2,15.014)}$=18.503, p<.001), and no interaction between MotorImpairment and Wearable ($Q_{(2,15.014)}$=0.033, p=.968, *n.s.*). Participants with upper-body motor impairments produced gestures that were 11% longer on average (4.60cm *vs.* 4.14cm) compared to the same gesture types entered by the participants without impairments with significant differences (p<.05, FWE controlled at α=.05) for each Wearable condition and the largest difference observed for stroke-gestures on the *ring* (4.51cm *vs.* 3.93cm, +15% longer paths); see Figure 4d.

4.4.3 Shape bending. Data deviated from normality for the *watch* condition and participants without impairments (p<.001) and heteroscedasticity was present for *glasses* (p<.002). We found a statistically significant main effect of MotorImpairment ($Q_{(1,9.661)}$=17.154, p<.005), a statistically significant effect of Wearable ($Q_{(2,10.702)}$ = 19.189, p < .005), and no interaction between MotorImpairment and Wearable ($Q_{(2,10.702)}$=3.371, p=.073, *n.s.*). Overall, participants with upper-body motor impairments articulated stroke-gestures that were two times more bent or "wavy" (53.71rad *vs.* 27.21rad, +97%) than the gestures produced by the participants without impairments with significant differences (p<.05, FWE α=.05) observed in all of the Wearable conditions; see Figure 4e.

4.5 Summary

Stroke-gestures produced by users with upper-body motor impairments on wearable touchscreens at various locations on the upper body are longer, wavier, less consistent, with more strokes, and take significantly more time to articulate compared to the same gesture types produced by users without impairments. Moreover, stroke-gesture articulation performance is influenced by the location of the wearable. Stroke-gestures performed in the *watch* condition were the fastest, least wavy, and with the highest consistency, while stroke-gestures articulated on the *ring* and *glasses* —two input conditions involving either high finger dexterity (*ring*) or manual dexterity and eyes-free hand and finger coordination (*glasses*)—exhibited significantly lower performance. Implications can be drawn for the difficulty perceived by users to execute gestures since longer production times, longer gesture paths, and more bending are known to correlate positively with perceived execution difficulty [78,97], but also on recognition accuracy [92] and the choice of the recognizer, e.g., a large number of strokes would make some recognizers, such as \$N [5], slow to execute.

5 RESULTS: MOTION-GESTURES

We report user performance with motion-gestures produced with the *finger*, *wrist,* and *head* corresponding to the *ring*, *watch*, and *glasses* conditions of Wearable. The data that we analyze is the

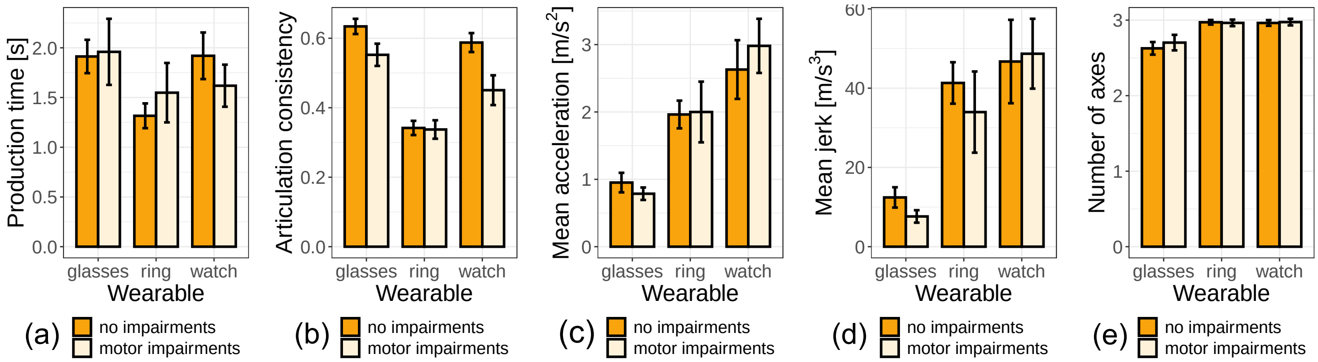

Figure 5: Characteristics of motion-gestures articulated by participants with and without upper-body motor impairments.

linear acceleration of motion-gestures, for which we first applied a high-pass filter to remove the effect of the force of gravity.[20]

5.1 Task Completion

We collected a total number of 3,809 gestures from a maximum of 4,032 trials = 3 (conditions for Wearable) × 6 (gesture types per set) × 28 (participants) × 8 (repetitions), representing an overall task completion rate of 94.5%. The completion rate was 100% for the participants without impairments and varied between 66.7% and 100% (M=88.9%, SD=15.5%) for the participants with upper-body motor impairments. Participants P_2 (traumatic brain injury) and P_6 (osteogenesis imperfecta) could not articulate motion-gestures in the *watch* condition, P_1 and P_8 (SCI C4-C5) could not move the fingers and, thus, did not enter gestures in the *ring* condition, and participant P_9 (Parkinson's) reported fatigue during the articulation of *head* gestures, of which she completed less than half of the trials. Table 1 shows the trial completion rate of each participant.

5.2 Gesture Production Time

Production time data deviated from normality for the *ring* condition and participants without impairments ($p<.05$) and heteroscedasticity was present ($p<.05$), so we used the Q test. We did not find a significant effect of MotorImpairment ($Q_{(1,11.514)}=0.215$, $p=.651$, *n.s.*), but we found a main effect of Wearable ($Q_{(2,12.033)}=17.476$, $p<.005$) with no interaction between MotorImpairment and Wearable ($Q_{(2,12.033)}=3.708$, $p>.05$, *n.s.*); see Figure 5a. The body part involved in the movement led to different gesture production times with statistically significant differences for participants with upper-body motor impairments between *glasses* and *ring* ($p<.001$) and *glasses* and *watch* ($p<.005$), respectively. Overall, participants with upper-body motor impairments were as fast as the participants without impairments to articulate motion-gestures (1.73s *vs.* 1.72s). Also, participants with upper-body motor impairments were faster by 16% (1.62s *vs.* 1.92s) at *watch* gestures, but the difference was not statistically significant ($p=.145$).

5.3 Gesture Articulation Consistency

ArticulationConsistency data was normal and homoscedastic, so we report the ANOVA F test. We found a statistically significant main effect of MotorImpairment ($F_{(1,22)}=17.818$, $p<.001$), a significant main effect of Wearable ($F_{(2,44)}=296.523$, $p<.001$), and a significant interaction between MotorImpairment and Wearable ($F_{(2,44)}=19.568$, $p<.001$). Overall, participants with upper-body motor impairments were less consistent in gesture articulation than the participants without impairments (0.45 *vs.* 0.52), with significant differences for *glasses* ($p=.010$) and *watch* ($p=.002$); see Figure 5b.

5.4 Kinematics of Motion-Gestures

5.4.1 Mean acceleration. Data was normal, but heteroscedasticity was present in the *ring* condition ($p<.005$). We found a significant main effect of Wearable on MeanAcceleration ($Q_{(2,13.184)}$ = 100.501, $p<.001$) with the largest difference observed for *watch* (2.98m/s^2 *vs.* 2.63m/s^2, $p<.05$). There was no effect of MotorImpairment ($Q_{(1,15.606)}=0.558$, $p=.466$, *n.s.*) nor an interaction between MotorImpairment and Wearable ($Q_{(2,13.184)}=2.681$, $p=.105$, *n.s.*). On average, motion-gestures were produced with the same acceleration magnitude by both participants with and without motor impairments (1.86m/s^2 *vs.* 1.85m/s^2); see Figure 5c. The body part involved in the movement, however, significantly affected acceleration in all conditions ($p<.05$, FWE controlled at $\alpha=.05$).

5.4.2 Mean jerk. Data was normal, but heteroscedasticity was present in the *ring* condition ($p<.05$). We found a significant main effect of Wearable ($Q_{(2,13.05)}=74.918$, $p<.001$), but no effect of MotorImpairment ($Q_{(1,14.975)}=0.098$, $p=.758$, *n.s.*) and no interaction between MotorImpairment and Wearable ($Q_{(2,13.05)}=1.615$, $p=.236$, *n.s.*). On average, motion-gestures were produced with the same jerk (28.91m/s^3 vs. 33.49m/s^3) by both participants with and without motor impairments; see Figure 5d. When employing Ruiz *et al.*'s [82] thresholds for classifying motion-gestures by jerk range,[21] we found that 2.44% of the gestures were *low* impulse, 11.11% were *moderate*, and 86.45% were *high* impulse, respectively.

5.4.3 Number of axes of movement. Data deviated from normality in the *ring* and *watch* conditions ($p<.05$). We detected a statistically significant main effect of Wearable ($Q_{(2,15.062)}=29.381$, $p<.001$), but no effect of MotorImpairment ($Q_{(1,14.129)}=1.178$, $p=.296$, *n.s.*) and no interaction between MotorImpairment and Wearable ($Q_{(2,13.891)}=0.367$, $p=.670$, *n.s.*). Motion-gestures were articulated on three axes for the *ring* (2.97 and 2.97) and *watch* (2.97 and 2.96),

[20] https://developer.android.com/guide/topics/sensors/sensors_motion

[21] Thresholds of 3m/s^3 and 6m/s^3 delimit *low, moderate,* and *high* impulse gestures [82].

and on two and three axes (2.70 and 2.63) for *glasses*; see Figure 5e. Multiple comparisons analysis (FWE controlled at α=.05) showed significant differences between *glasses* and *ring* (p<.001) and *glasses* and *watch* (p<.05) for both participants with and without upper-body motor impairments.

5.5 Summary

Motion-gestures were produced equally fast and with similar kinematic characteristics by both participants with and without motor impairments. The results on the kinematics of motion-gestures complement the findings on gesture production times, e.g., faster gestures in the *watch* condition are explained by higher acceleration produced by users with motor impairments. Overall, there seems to be similar performance with motion-gesture articulation with wearables for both groups of participants, unlike for stroke-gesture input (see Section 4), a finding that is corroborated across multiple dimensions of motion-gesture analysis. The wearable location did affect gesture articulation, but in a way that was similar to both groups of participants. Motion-gestures with the *finger* and *wrist* were faster than *head* gestures, but also less consistent.

6 DISCUSSION

We discuss our findings from the perspective of individual users' performance with stroke-gesture and motion-gesture input. We also propose implications for accessible gestures for wearables by capitalizing on the principles of ability-based design [101].

6.1 A Glimpse into Individual Users' Performance with Gesture Input

The approach to gesture analysis that we adopted in this work was to report overall user performance across a variety of gestures, which we interpreted as a sample drawn from all possible gesture types. To this end, our choice of stroke-gestures and motion-gestures was carefully considered during the experiment design to cover gesture types with a diversity of characteristics; see Subsection 3.4 for our rationale. Evidently, some of the gestures from our set are easier to execute, faster to execute, or are articulated with higher consistency compared to other gesture types. To identify gestures with such desirable characteristics, the practitioner can chose one or several measures of gesture performance relevant to their goal, e.g., ProductionTime to identify fast gestures, in order to inform design decisions about which gesture types to include in the user interface. Next, we present an example of such a pursuit. Our goal is not to provide a detailed analysis, but rather to demonstrate how such an analysis could be accomplished.

Figure 6 shows rankings that we computed for the 30 gesture types used in our experiment according to the ratio of ArticulationConsistency and ProductionTime, a combined measure that we employ for demonstration purposes. The higher the articulation consistency and the lower the production time of a gesture, the better the ranking that gesture receives. Using this measure, we ranked stroke-gestures from 1 to 12 (1 is better) and motion-gestures from 1 to 6 (1 is better) for each Wearable. A few observations are interesting to note. For instance, directional swipes generally ranked first (1 and 2), but variations involving rankings 1 to 4 can be observed for *glasses* and *ring*, highlighting difficulties with producing straight paths in those conditions. Also, "six-point star," "asterisk," and "heart" are among the lowest ranked stroke-gestures for both users with and without motor impairments, which confirms their difficulty, as estimated during our experiment design (Figure 3). Other stroke-gestures also ranked low for some of the participants with upper-body motor impairments, e.g., "circle" for P_2 (traumatic brain injury), P_3 (SCI), and P_{12} (Friedreich's ataxia) ranked on the 10th position for *glasses*, but between 4th and 7th for *ring* and *watch*, showing different levels of performance of the same gesture type with wearables at different locations on the upper body. Regarding motion-gestures, circular movements of the *head* and double taps performed with the *finger* ranked low, while leaning the *head* forward and tapping with the *wrist* received good rankings overall.

Our results also showed that some combinations of gesture modalities and locations of wearables on the upper body were not feasible for all of the participants with upper-body motor impairments. For example, participants P_1, P_8, and P_{14} did not enter stroke-gestures in the *ring* condition because they could not move their thumb (SCI at vertebrae C4-C5 for P_1 and P_8) or did not have the thumb (P_{14}, phocomelia), while P_7 (multiple sclerosis), P_8 (SCI), and P_9 (Parkinson's) could not raise their arms to the *glasses*. Other participants with upper-body motor impairments adopted coping strategies to enter stroke-gestures, which resulted in the larger production times that we observed compared to the same gesture types articulated by the participants without impairments. For instance, P_{11} (spastic quadriplegia) hold the temple of the glasses between their thumb and middle fingers and entered stroke-gestures with the index. While she was able to produce stroke-gestures that way, the average production time was 4.58s, a value 40.5% larger than the average obtained across all of the participants with upper-body motor impairments and 288.1% larger than the average production time of the participants without impairments (see Figure 4a). To enter stroke-gestures on the *ring*, P_4 repositioned the device at the knuckle of the index finger for more stability and control, and performed the gestures on the part of the touchscreen where it was easier to reach with the thumb. P_{12} (spastic quadriplegia) preferred to held the *glasses* with the other hand to keep them stable, and P_9 and P_{13} (Parkinson's) held the *ring* steadily with the other hand while entering stroke-gestures with the thumb.

These qualitative observations indicate that different motor abilities lead to different levels of performance with stroke-gesture and motion-gesture input for *rings*, *watches*, and *glasses*, but also to different types of coping strategies to use gesture input on these devices. To understand more about individual differences between users, Figure 7 shows the results of a clustering process[22] of the gesture input performance of the fourteen participants with upper-body motor impairments characterized by the combined ArticulationConsistency and ProductionTime ratio measure. Several observations are interesting to note. For instance, participants P_{11} and P_{12} (spastic quadriplegia) exhibited similar performance when articulating stroke-gestures in the *glasses* and *ring* conditions, and are part of the same cluster (height of cutting the dendrogram h=0.17[23]) for the *watch* condition; participants P_1 and P_8 (same

[22] Agglomerative hierarchical clustering with average linkage.
[23] This value corresponds to the average ArticulationConsistency and ProductionTime observed for the participants with upper-body motor impairments, i.e., 0.55/3.16 = 0.17 for stroke-gestures; see Section 4.

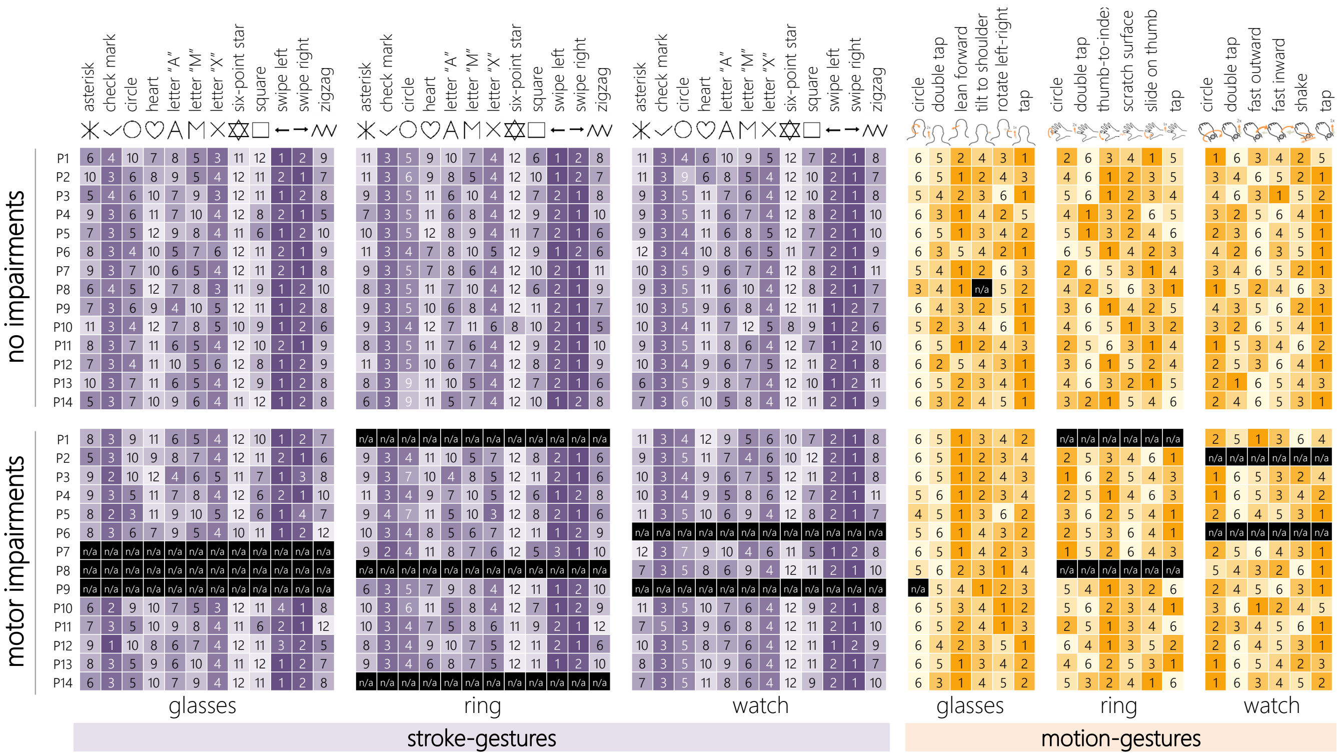

Figure 6: Rankings of stroke-gestures from 1 to 12 (1 is better) and motion-gestures from 1 to 6 (1 is better) according to their combined ProductionTime and ArticulationConsistency characteristics; see Figure 3 for the gesture descriptions.

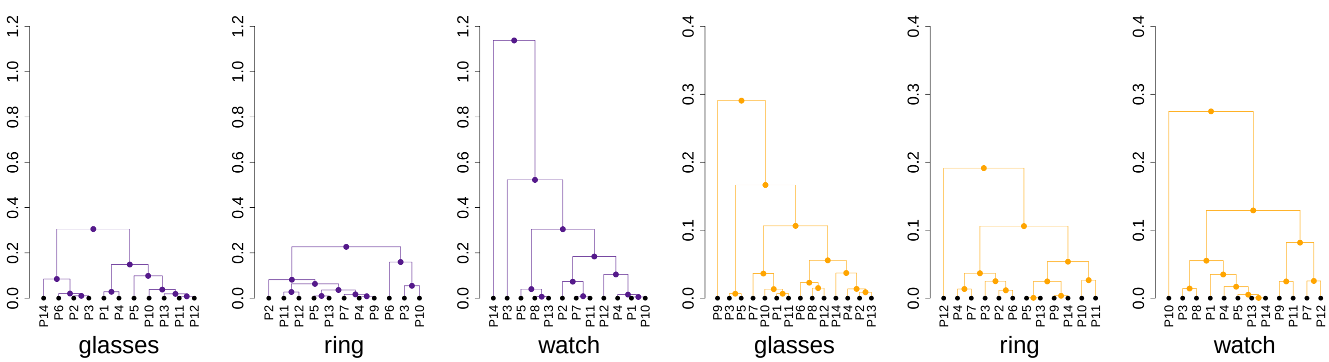

Figure 7: Clusters of participants with upper-body motor impairments according to their input performance with stroke-gestures (the three dendrograms on the left) and motion-gestures (the three dendrograms on the right), characterized conjointly by the ArticulationConsistency and ProductionTime measures.

condition of SCI C4-C5) also fall in the same cluster (h=0.17) for the *watch* condition. For motion-gestures, P_9 and P_{13} (Parkinson's) had similar performance with both the *ring* and *watch* devices, but the different severity of their conditions (see Table 1 for their self-reported impairments with eight categories for P_9 *vs.* five for P_{13}) led to different levels of performance with *glasses* gestures, where P_9 completed less than half of the experiment trials. This aspect is observable in the fourth dendrogram from Figure 7. Another aspect resulting from the composition of the clusters regards the effect of the Wearable on the gesture input performance of the participants with upper-body motor impairments. For instance, by cutting the stroke-gesture dendrograms at h=17,[23] two clusters result for *ring* and *glasses* (with slightly different compositions of participants) compared to five clusters for the *watch*.

Although the examination of the relative differences between users is interesting, we stop this analysis here, but practitioners interested in specific gesture types can continue such examinations, including with other gesture characteristics, e.g., NumStrokes for stroke-gestures as in [4,92] or MeanJerk for motion-gestures as in [82], or combinations thereof as in our example in order to identify gestures that are articulated efficiently by all users or gestures that work well for users with specific motor abilities towards personalized gesture UIs. Our freely available datasets enable such examinations. Next, we continue our discussion by employing Wobbrock *et al.*'s [101,102] framework of ability-based design to derive more general implications for accessible gestures for wearables.

6.2 Ability-based Design for Accessible Gesture Input With Wearables

Our findings suggest the need for design approaches that capitalize on users' specific motor abilities. Ability-based design [101,102] emphasizes the importance of focusing on *users' abilities in context* to deliver accessible interactions with computer systems based on seven principles: *ability, accountability, availability, adaptability, transparency, performance,* and *context.* In our case, abilities refer to gross and fine motor skills in finger, wrist, arm, and neck muscles to perform stroke-gestures and motion-gestures on and with *rings*, *watches*, and *glasses*. In the following, we present ten practical implications informed by our empirical findings, that we propose to implement the principles of ability-based design towards accessible gesture input for these wearables.

According to the *ability* principle [101], designers should focus on users' abilities in a given context. Our findings suggest:

❶ Design gesture sets that include stroke-gestures, motion-gestures, and combinations thereof according to the motor ability of the user to move fingers, land the finger on a surface, maintain stable contact with the surface to produce a gesture path, rotate the wrist, produce accelerated movement, raise the hand, and control cervical muscles. *Example:* P_{14} could not perform stroke-gestures on the *ring* because of missing thumbs (phocomelia), but was able to move the finger wearing the ring to produce motion-gestures (Table 1).

❷ Design customizable devices in terms of the location on the body where they are worn to enable comfortable reaching for stroke-gesture input and effortless motion-gestures with movements of that body part. *Example:* P_7 could not raise the hand to perform stroke-gestures on the *glasses* (see Table 1), but was able to use the same type of gestures on the same device worn in the form of a *watch* and a *ring*, respectively.

The *accountability* principle [101] states that designers change systems, not users to foster usability. Accordingly, we propose:

❸ Adapt to user's abilities by short-cutting input. *Example:* wearables could implement gesture prediction, abbreviation, and autocompletion [9,15] from partially entered gestures to make input faster, since users with upper-body motor impairments take twice as much time to articulate stroke-gestures compared to users without impairments (Figure 4a).

❹ Reuse accessible gesture sets across devices and from existing devices to new devices. *Example:* stroke-gestures can be performed effectively on touchscreens affixed to various parts of the body as long as the device can be comfortably reached (see similar rankings for some of the stroke-gesture types in Figure 6) and, thus, could be reused across multiple devices, including for new wearables that a user acquires or that may become available in the future. Also, smartphone stroke-gestures, evaluated in [96] as an effective input modality for users with upper-body motor impairments, could also be reused for input with wearables.

Following the *availability* principle [101], designers use affordable and available software and hardware. As smartwatches and fitness trackers are becoming mainstream [98], requirements regarding their affordability and availability are met implicitly. Smart rings and glasses, however, are still to become largely adopted. Until then, a practical solution to affordability and availability is to:

❺ Reuse the touchscreen of a smartwatch, a prevalent wearable, and affix it to various parts of the body for easier and more convenient access with the finger or for instrumenting that body part for motion-gesture input. *Example:* P_6 could not enter stroke-gestures on the *watch* (see Table 1), but was able to use the watch repurposed as a *ring* and touchpad on the *glasses* temple. Khurana *et al.* [50] discussed options for morphing smartwatch displays into various forms, after detaching from the straps, towards "a better interaction device, better display, and a better sensor suite" (p. 50:1). In our context, "better" translates to easier to reach, touch, pinch, grasp, move, rotate and, in general, to a more accessible device.

According to the *adaptability* principle [101], interfaces provide the best possible match to users' abilities. Based on our findings, our proposed practical implementation for this principle is:

❻ Allow gesture commands to be personalized to how users execute them in terms of the geometric characteristics of the gesture path (Figures 4c to 4e), e.g., stroke-gestures with various numbers of strokes, or kinematic characteristics of the underlying movement (Figures 5c to 5e), e.g., different jerk magnitudes, by using articulation-independent gesture recognizers [71,91]. *Example:* "letter X," a two-stroke gesture, could also be performed in one continuous movement with the two lines joint by an intermediate stroke, removing the need for the finger to lift off of the screen after the first stroke, travel in air, and then land again on the screen to continue the gesture. Other options include enabling users to define gestures according to their preferences and motor abilities and also enabling personalized mappings between gestures and system functions according to their preferences [63].

Transparency [101] means that interfaces give users awareness of their adaptive behaviors. Our results inform the following:

❼ Provide feedback and feedforward during gesture input. *Example:* participants with upper-body motor impairments take more time to produce stroke-gestures (Figure 4a). In that case, feedback about the process of gesture sensing and recognition [48,52], e.g., the system gently informs that it is patiently waiting for the gesture to be fully articulated, is likely to increase usability and provide the user with the means to inspect, discard, revert, and correct the outcome. Also, feedforward [22] to guide users during stroke-gesture [8] and motion-gesture [23] input could be used in conjunction with guideline ❸ to make gesture input faster.

According to the *performance* principle [101], systems employ users' performance for best match with abilities. We suggest:

❽ Model the user's gesture articulation behavior. *Example:* more time to produce a stroke-gesture (Figure 4a), more strokes to draw the geometric shape of a stroke-gesture (Figure 4c), and performing motion-gestures along preferred axes of movement (Figure 5e) are examples of information that the wearable device could collect and use to tune the UI settings, e.g., how long to wait for a multistroke gesture to be entered before calling the gesture recognizer.

Following the *context* principle [101], systems utilize users' context to accommodate effects on abilities. Our proposed practical implementations of this principle for wearable interactions are:

❾ Infer the context of use to switch to input modalities better suited to that context. *Example:* accommodate gesture input that is socially acceptable [79] for interactions involving wearables that do not draw attention to one's disability [76] by switching from motion-gestures in mid-air to stroke-gestures on the device and vice versa.

❿ Design wearables that share information among each other. *Example:* multiple devices share gesture sets to enable users to employ the same gestures and, consequently, easily switch between input devices according to context.

7 LIMITATIONS

There are a few limitations to our study. First, we asked participants to produce stroke-gestures with the thumb of the same hand in the *ring* condition and the with the hand located on the same side of the body as the temple of the *glasses* to which the touchscreen was affixed, since these articulations implemented different motor ability requirements and corresponding assumptions; see Subsection 3.2. However, this constraint resulted in some of the users with upper-body motor impairments not being able to participate in all of the conditions of our experiment. We acknowledge that in real life coping mechanisms would intervene, e.g., using the other hand, other fingers, and other body parts [42,57] to implement the interaction. Future work is recommended to examine such mechanisms. Second, we used the same device in all of the conditions of our experiment. While this choice enabled us to collect gestures consistently with finger, wrist, and head wearables, the form factor of the device was large for the *ring* condition, which might have impacted users' articulations. Future work is recommended with smaller touchpads worn on the finger. Third, it was not our goal to evaluate gesture recognition accuracy and, thus, we allowed participants to enter gestures as they wished, which provided great flexibility during input and enabled us to observe unconstrained user behavior during gesture articulation. For example, we did not constrain participants to a specific number of strokes or stroke ordering when entering stroke-gestures, although such a constraint would actually help some gesture recognizers, such as $1 [104] for stroke-gestures and $3 [53] and Jackknife [86] for motion-gestures, to increase accuracy. Future work on the recognition of gestures produced by users with upper-body motor impairments is envisaged as well as correlation analysis between recognition accuracy results and gesture performance measures as in [92]. To address these limitations, we provide in the following several ideas for future work as well as free resources to support their implementation.

8 CONCLUSION AND FUTURE WORK

We examined gestures performed by users with upper-body motor impairments with devices worn on the *finger*, *wrist*, and *head* in the form of *rings*, *watches*, and *glasses*. Our results showed that stroke-gestures are more challenging to produce under conditions of upper-body motor impairments, but articulations of motion-gestures presented similar characteristics for both users with and without impairments. Based on our empirical findings, we proposed ten implications of the principles of ability-based design towards more accessible gesture input for wearable interactions.

To enable future work in this area, we release our two datasets composed of 7,290 stroke-gestures and 3,809 motion-gestures collected from 28 participants. The datasets are available for research purposes from http://www.eed.usv.ro/~vatavu together with C# source code that computes the measures reported in this paper. Given the lack of public data for users with upper-body motor impairments [21,61], we see several opportunities that these datasets open for future work on accessible wearable interactions: (1) compare stroke-gesture input on small wearables to stroke-gestures articulated on smartphones and tablets with larger touchscreens [96];[24] (2) evaluate the accuracy of popular gesture recognition approaches [86,91,104] and explore, if needed, adaptations of these approaches [71] for the gesture articulation characteristics of users with upper-body motor impairments; (3) conduct further examinations with other gesture analysis tools and measures, such as heatmap visualizations [93], to complete our understanding of users' gesture input performance with wearables. These future work directions can be readily implemented by using our datasets, and we look forward to new findings and developments towards more accessible wearable interactions for users with all motor abilities.

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