An Expressivity-Complexity Tradeoff?: User-Defined Gestures from the Wheelchair Space are Mostly Deictic

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ABSTRACT

We present empirical results about gesture expressivity and articulation complexity from an analysis of 231 gestures elicited from eleven wheelchair users, for which we employ a combination of McNeill's gesture theory from psycholinguistics and a taxonomy used in Human-Computer Interaction for the analysis of gestures elicited from end users. We report that 53.7% of the gestures that we analyzed were deictic in nature, and 50.7% were performed toward the body. These findings suggest a potential tradeoff between the expressivity of iconic and metaphoric gestures, less represented in the gesture set analyzed in this work, for the low complexity of simple pointing movements performed from the wheelchair space. Our results complement findings of previous gesture elicitation studies conducted with users with motor and/or mobility impairments, and suggest future work opportunities for gesture input performed from the wheelchair space, including mixed-nature gestures that feature both low complexity and rich expressivity.

CCS CONCEPTS

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

KEYWORDS

Gesture input, wheelchair users, motor impairments, mobility impairments, deictic gestures, iconic gestures, gesture elicitation

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1 INTRODUCTION

There is a rich scientific literature documenting the ways in which people with motor and/or mobility impairments experience accessibility challenges when interacting with computer systems, including mobile and wearable devices [8,20], switching between devices and using devices while moving [7], interacting with television [29], using touch input on large multitouch tables [9] and public ambient displays [32], and entering text [39] and playing motion-based games [13] from the wheelchair. These challenges have been addressed with specific technical solutions, among which solutions based on gesture input [3,31] are one convenient opportunity for accessible interactions due to the variety of gesture types that can be sensed with off-the-shelf technology, following the "ability" and "availability" principles of ability-based design [37].

Gesture input from the wheelchair space includes gestures performed with mobile [8] and wearable [30] devices, gestures of the hand performed in mid-air [3], on the body [20], the wheelchair armrest [6], and "above-the-neck" gestures [40], respectively. These examples show a diversity of gesture types of rich expressivity, and the application domains are multiple and varied, including wheelchair control [16,17], gesture-controlled robotics [1,15,28], and interacting with public ambient displays [32] and services [30]. However, prior work has reported that accessible gestures elicited from people with motor and/or mobility impairments are mostly simple, i.e., simple head movements and eye blinks [40], taps and single-stroke swipe gestures [19], and gestures performed in easily accessible regions on and around the body [3]. These results show a preference for low-effort, low-complexity gestures, and suggest a potential tradeoff between the rich expressive capabilities of gesture input [5,27] and gesture articulation complexity.

To examine this potential tradeoff, we use a combination of McNeill's [21] gesture theory from psycholinguistics, focused on understanding gestures as images with which people "display their inner thoughts and ways of understanding events of the world" [21, p. 12], and a taxonomy from HCI used for gesture elicitation studies [38], focused on obtaining "a detailed picture of user-defined gestures and the mental models and performance that accompany them" [38, p. 1083] for the purpose of interacting with computer systems. We present empirical results about the expressive nature and articulation complexity of user-defined gestures performed from the wheelchair space by analyzing a public dataset of 231 gestures proposed by eleven wheelchair users with various motor impairments and health conditions [3]. We report more preference for *deictic* (53.7%) and simple *symbolic* (26.0%) gestures, e.g., hand poses and directional swipes, instead of gestures bearing *iconic* (14.3%) or *metaphoric* (6.0%) connotations, in McNeill's [21] sense, findings that show the presence of the expressivity-complexity tradeoff in our dataset. Based on our findings, we propose future work opportunities for gesture input performed from the wheelchair space, such as designing gesture sets in accordance with the body image representation and malleability of the peripersonal space, which

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may incorporate the wheelchair, as well as mixed-nature gestures that are both low complexity and expressively rich, e.g., deictic gestures that also have metaphorical connotations.

2 RELATED WORK

Previous work has examined gesture input from the wheelchair space and involving the wheelchair. Malu and Findlater [20] reported accessibility challenges experienced by users with upper-body motor impairments to lift the arm to the touchpad of Google Glass, and proposed switch-based input using a touchpad that could be affixed by the user at a convenient location on their body or wheelchair. Wobbrock *et al.* [39] proposed gesture-based text entry methods for the joystick and touchpad designed to be used from the power wheelchair. Carrington *et al.* [8] coined "chairables" to denote devices designed to fit with the form of the wheelchair and be used from the wheelchair space, just like wearables fit with an individual's clothing, and explored possibilities for their placement and form factors. An example is "Gest-Rest" [6] chairables that fit over a standard wheelchair armrest to enable touch gesture input.

In this work, we primarily connect to the practice of gesture elicitation studies [38], where participants propose gestures in response to system functions, known as "referents." For details about implementing such studies, we refer readers to Wobbrock *et al.* [36,38], who proposed the method, and to Vatavu and Wobbrock [34] for an overview of gesture analysis models. Despite the popularity [35] of such studies for unveiling users' preferences for gesture input, only few gesture elicitation studies have been conducted with users with motor and/or mobility impairments [3,19,23,40]. For instance, Roy *et al.* [23] elicited gestures from people with Cerebral Palsy in response to concepts of weight, emotion, character formation, and object visualization, and trained a neural network to recognize gestures reflecting users' physical abilities. Malu *et al.* [19] elicited more accessible smartwatch gestures from users with upper-body motor impairments. Zhao *et al.* [40] examined users' preferences for above-the-neck gestures, e.g., gestures performed with head and eye movements, to effect common functions on smartphones. Bilius *et al.* [3] conducted a gesture elicitation study with wheelchair users and a set of twenty-one referents, and found a large preference for on-body (47.6%) and in-air (40.7%) gestures, primarily performed with one hand in the center and upper periphery regions around the body. The gestures reported by these studies have been mostly simple, performed in easily-accessible regions on and around the body, highlighting a common sense preference for low-effort, low-complexity input. We wonder to what extent the richer expressiveness of other gesture types, more complex in terms of their articulation and meaning [21], has been traded off by participants seeking simple gestures. If this were the case, this expressivity-complexity tradeoff might have caused missed opportunities for discovering highly-expressive gesture input.

3 STUDY

We conducted an exploratory analysis of the combined nature and articulation complexity of user-defined gestures performed from the wheelchair space by using Bilius *et al.*'s [3] public gesture dataset. After a brief description of the dataset, we present our procedure.

3.1 Dataset

Bilius *et al.* [3] collected a dataset of 231 gestures performed by eleven wheelchair users with various motor and mobility impairments[1] with the goal of understanding user preference for on-body, in-air, and on-wheelchair gestures to control interactive systems. Following the end-user elicitation method [38], the gestures were elicited in response to twenty-one system functions (e.g., "access email," "turn on/off the TV," "next," etc.) representing the conditions of the Referent independent variable. Participants were instructed to perform the gestures however they wanted: on their body, including clothes, in the air around the body, or on various parts of the wheelchair, and using their preferred hand or both hands. Referents were presented with short sentences on a computer screen, and randomized per participant. Referents were also grouped into three categories (*Actions*, *Content*, and *Navigation*), according to their type, representing the Referent-Category variable. We refer readers to Bilius *et al.* [3] for more details. The dataset consists of: (i) text descriptions of the participants' gestures, formatted as a CSV file with 231 lines, one line per gesture, indexed by Referent and Referent-Category, (ii) a description of participants' motor symptoms using the eleven categories from Findlater *et al.* [10], e.g., slow movements, fatigue, lack of sensation, etc., and (iii) R code that reads the dataset and reports the on-body, in-air, and on-wheelchair gesture measures analyzed in [3]. These resources can be freely downloaded from the dataset web page;[2] see Figure 1 for a few gesture examples. Although other studies [19,23,40] have elicited gestures from people with motor and/or mobility impairments, Bilius *et al.*'s [3] dataset is the only public data on this topic.

3.2 Procedure

We extracted information about the nature and articulation complexity of user-defined gestures proposed from the wheelchair space. For the video analysis, we adopted McNeill's [21] coding scheme for transcribing and coding gesture characteristics from videos (pp. 375-382) and a corresponding dimension from Wobbrock *et al.*'s [38] taxonomy for analyzing user-defined gestures, from which we selected the following measures relevant to our goal:

- Gesture-Nature, nominal variable with four categories of gesture expressivity: *iconic*, *metaphoric*, *deictic*, and *symbolic*. The first three[3] categories are from McNeill's [21] gesture theory: iconics picture a concrete object or event (e.g., the hand mimics holding a TV remote control), metaphorics depict an abstract idea (e.g., the hands rise up to suggest the genre of the TV content), and deictic gestures are pointing movements used to indicate to both concrete and imaginary objects and/or locations. To these categories, we added *symbolic* gestures, e.g., iconics that depict a symbol, such as letter "S" or a circle drawn in mid-air, by following Wobbrock *et al.*'s [38] "nature" dimension, popular in gesture elicitation studies. Symbolic gestures are essentially *iconic*, but we consider them distinctly due to their relevance for implementing

[1] Spinal Cord Injury, Traumatic Brain Injury, Spina Bifida, Osteogenesis Imperfecta, Multiple Sclerosis, Parkinson's, Cerebral Palsy, Friedreich's Ataxia.
[2] http://www.eed.usv.ro/~vatavu/projects/2023-GESTURES-BAW
[3] We ignored McNeill's [21] "beats" and "cohesives" in our analysis since they accompany speech, not relevant to our scope.

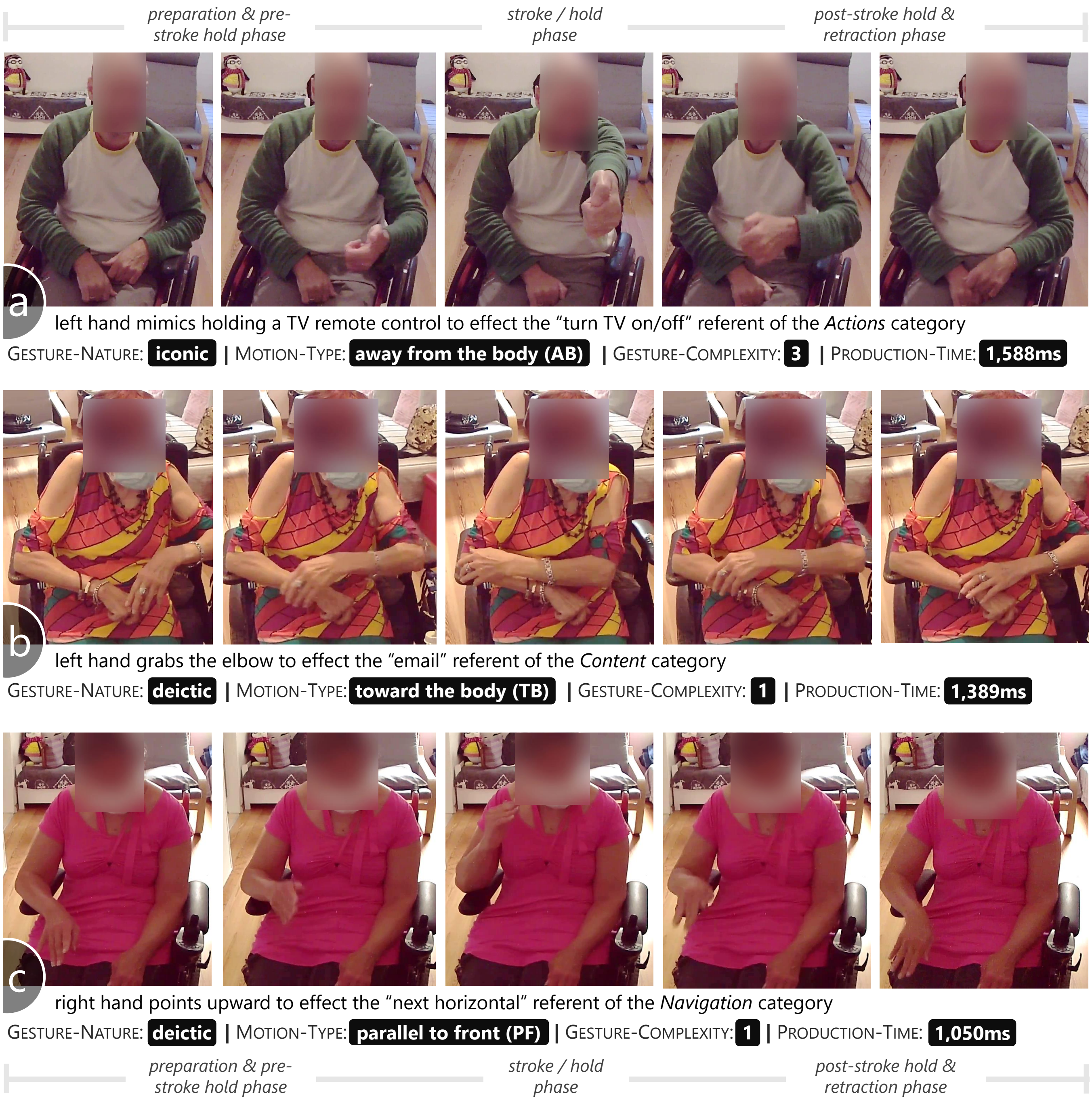

Figure 1: Three examples of gestures from the dataset [3] analyzed in our study, corresponding to referents from the *Actions*, *Content*, and *Navigation* categories: (a) a gesture proposed by a person with Multiple Sclerosis to effect "turn TV on/off," (b) a gesture proposed by a person with Parkinson's to access "email," and (c) a gesture proposed by a person with Cerebral Palsy to effect "next horizontal." The gesture articulation phases, from preparation to retraction [21], are also illustrated.

gesture-based commands for interactive systems, e.g., letter "S" can act as a mnemonic shortcut [24] for system functions that start with "S," such as "Save," "Search," "Select," while "thumbs-up," a culturally-dependent gesture of the hand, can be used to answer affirmatively and provide confirmation to the system about the last action, event, or notification.

- GESTURE-COMPLEXITY, interval variable, computed following a method from McNeill [21, p. 385] by counting any of the following elements of gesture articulation: (i) the gesture is articulated with both hands, (ii) the gesture implies finger movements, (iii) the gesture implies the hand changing position during articulation, (iv) hand position is other than "open" or "closed hand," and (v) the gesture implies the movement of the hand from the rest position. Gesture-Complexity evaluates as an integer between 1 (low) and 5 (high complexity). We adopted McNeill's definition of gesture complexity since it involves objective evaluation criteria compared to the approach used in end-user gesture elicitation studies, which relies on subjective assessments of referents' conceptual complexity [38]. Figure 1 and the last paragraph of this section present a few calculation examples.

To complement these measures, we also extracted information about the underlying motion of the gesture, as follows:

- Motion-Type, nominal variable with four categories, specifies the direction of the gesture with respect to the user's body. Following McNeill [21, p. 380], we distinguished among gestures performed *toward the body (TB), away from the body (AB), parallel to front (PF),* and *parallel to side of the body (PS).* Complementary to Gesture-Nature, the direction of motion is useful to situate gestures of a given nature, e.g., *iconic* or *deictic*, in the personal (TB), peripersonal (PS and PF), and extrapersonal (AB) space of the wheelchair user.
- Production-Time, in milliseconds, measured as the difference between gesture start and stop timestamps extracted from the video recordings. Production-Time is a key measure of user performance [4,18], which associates positively with the perceived difficulty of gesture input [33].

The Gesture-Nature, Gesture-Complexity, and Motion-Type information was extracted independently by two researchers and the results were confronted. Gwet's AC1 [14] inter-reliability coefficients were .715, .995, and .756, respectively (with the cumulative membership probabilities .999, 1, and 1), corresponding to consensus levels between "substantial" and "perfect," according to the Landis-Koch benchmarking scale.[4] To measure Production-Time, we wrote a Python script to approximate gesture start and stop timestamps using a motion detector based on the difference between consecutive frames, after which we manually extracted the timestamps more precisely using the video player seek bar.

Figure 1 exemplifies three gestures from the dataset. The first gesture mimics holding an imaginary TV remote control and, thus, is *iconic*, performed *away from the body,* and has a complexity score of 3 (i.e., +1 since finger movements are used to press the buttons of the imaginary TV remote control, +1 since the hand changes shape during the gesture articulation, and +1 since the hand moves from the rest position). The second gesture is represented by the left hand grabbing the right elbow, which is a *deictic* gesture performed *toward the body* with a complexity score of 1 (the hand moves from the rest position, but does not change form). The third gesture, represented by the right hand pointing upward, is also *deictic* but, unlike the second gesture, does not involve physical contact with any object or body part.

[4]https://cran.r-project.org/web/packages/irrCAC/vignettes/benchmarking.html

3.3 Design

We are interested in gesture nature and articulation complexity overall, for all the elicited gestures, but we also present results according to the Referent and Referent-Category variables; see Figure 2 for their corresponding categories.

4 RESULTS

We report findings about the expressive nature and complexity of user-defined gestures performed from the wheelchair space. To this end, we analyze Gesture-Nature in relation to Gesture-Complexity to examine the possible tradeoff between the semantic expressivity of a gesture (e.g., users resorting to metaphors when referring to specific referents) and the complexity of its articulation. We complement these results with Motion-Type, as the spatial and directional description of a gesture in relation to the user's body, along with the Production-Time needed to articulate the gesture.

4.1 Gesture Nature and Complexity

We found that *deictic* gestures were the most frequently proposed (53.7%), followed by *symbolic* (26.0%), *iconic* (14.3%), and *metaphoric* (6.0%) gestures; see Figure 2a. A Friedman test revealed a statistically significant effect of Referent-Category on Gesture-Nature ($\chi^2_{(3)}$=14.471, p=.002), and post-hoc Wilcox signed-rank tests (Bonferroni corrected α=.05/6=.0083) confirmed significant differences between *deictic* and *metaphoric* gestures (Z=2.807, p=.006). Figure 2a also presents detailed results for each Referent, showing that *deictic* gestures were the majority preference for seventeen of the twenty-one referents (81.0%) for which gestures were elicited from wheelchair users. Exceptions were the "place call," "answer call," and "turn TV on/off" referents, for which most of the gestures were *iconic* (e.g., mimicking a phone or a TV remote control) and "undo," for which more *symbolic* gestures were proposed. Most of the symbolic gestures were simple, represented by hand poses, e.g., "thumbs up," "open hand," "fist," etc., and directional swipes.

To understand the preference for *deictic* gestures, we look at Gesture-Complexity, which varied between 1 and 4 (M=1.7, SD=0.4) on a scale from 1 (low) to 5 (high); see Figure 2b. Complexity scores were overall low, with 88.3% of the gestures consisting in either one or two elements of articulation complexity, according to McNeill's [21] calculation method. The gestures proposed for the referents of the *Actions* category exhibited the highest complexity (M=1.8, SD=0.6) and those of *Navigation* the lowest (M=1.5, SD=0.4), but a Friedman test did not detect a statistically significant effect of Referent-Category on Gesture-Complexity ($\chi^2_{(2)}$=1.722, p=.423, *n.s.*). Of the *deictic* gestures, just 16.9% were contactless, represented by pointing in mid-air (an example is illustrated in Figure 1c), while 83.1% involved physical contact with the part of the body (61.3%) or wheelchair (21.8%) indicated by the gesture. Figure 3 illustrates linear correlations between Gesture-Complexity and specific Gesture-Nature categories. We found a statistically significant[5] negative linear correlation with the percentage of observed *deictic* gestures ($r_{(11)}$=−.683), and a positive correlation with

[5]To determine statistical significance, we use 95% CIs of Pearson's r correlation coefficient computed with bootstrapping with N=2,000 samples.

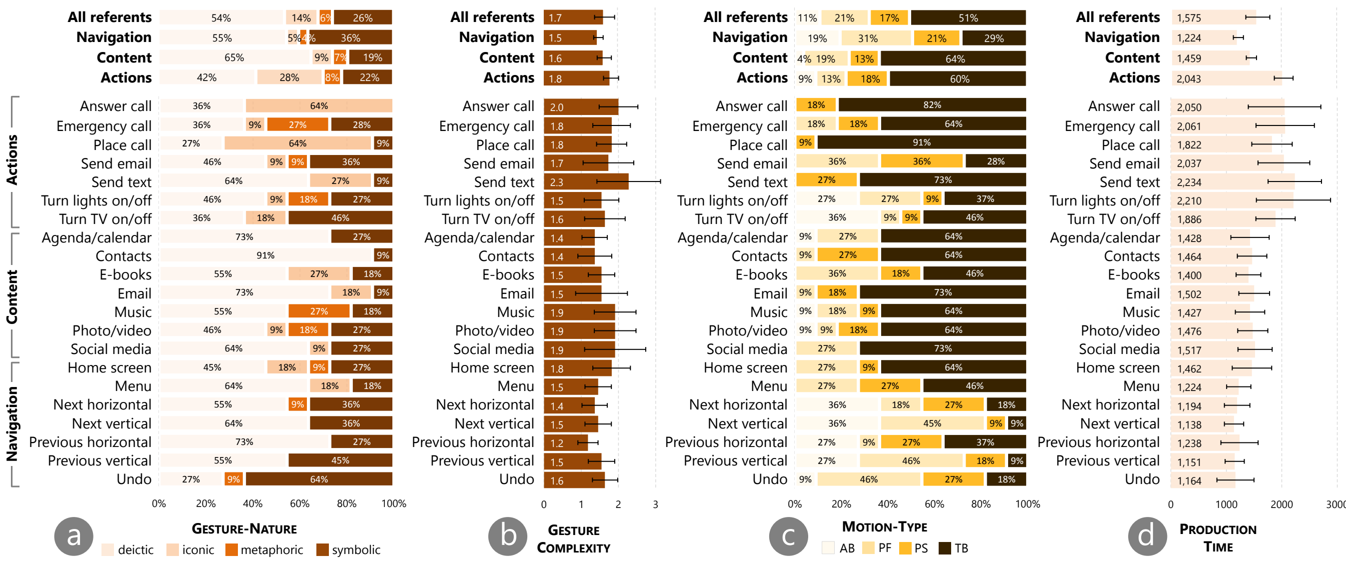

Figure 2: Nature, complexity, motion type, and production time of user-defined gestures. Note the large proportion of *deictic* gestures (54%) and movements *toward the body* (51%), fast articulations (M=1.58s), and gestures of low complexity (M=1.7).

the percentage of *iconic* gestures ($r_{(11)}$=.664). These results, corroborated with the percentages of *deictic* (53.7%), *symbolic* (26.0%), and *iconic* (14.3%) gestures, suggest that the rich expressiveness of iconics was traded off for simple, low-complexity pointing movements.

4.2 Gesture Motion and Production Time

Half of the user-defined gestures were performed *toward the body* (50.7%) compared to *parallel to front* (21.2%), *parallel to side* (17.3%), and *away from the body* (10.8%), respectively; see Figure 2c. A Friedman test detected a statistically significant effect of Referent-Category on Motion-Type ($\chi^2_{(3)}$=14.915, p=.002), and post-hoc Wilcox signed-rank tests revealed significant differences (Bonferroni-corrected α=.05/6=.0083) between the TB and AB (p=.004), and TB and PS (p=.007) categories, respectively. Figure 2c also shows Motion-Type results for the individual referents.

Gesture Production-Time varied between 1007ms and 2116ms (M=1575.4ms, SD=322.5ms); see Figure 2d. A Friedman test detected a significant effect of Referent-Category on Production-Time ($\chi^2_{(2)}$=10.364, p<.01), and post-hoc Wilcoxon signed-rank tests revealed significant differences (Bonferroni-corrected α=.05/3=.0167) between the *Actions* (M=2043.0ms, SD=682.1ms) and *Navigation* (M=1224.3ms, SD=298.5ms) referents (p=.005). We did not find significant correlations between Production-Time and the observed percentages of the Motion-Type gesture categories; see Figure 3.

These results complement our findings about the expressive nature and complexity of user-defined gestures with specific nuances. For example, gestures performed *toward the body* and *parallel to side* were mostly *deictic* (34.2% and 12.6%), used to indicate in the personal and peripersonal space of the body and wheelchair. Gestures performed *away from the body* contained an equal number of *deictic* and *symbolic* gestures (4.3%), while gestures *parallel to front* were mostly *symbolic* (14.7%), revealing the convenience of the peripersonal space for articulating swipes and stroke-gestures.

4.3 Qualitative Findings

The videos of the dataset occasionally contained participants' brief comments about the gestures they proposed, which we use in the following to complement our quantitative findings.

Deictic gestures performed *toward the body* were chosen by the participants in relation to specific meanings they attributed to specific body parts. For example, P_4 positioned his hand near the heart to access "e-books," and said "I made this gesture because I really love reading," while P_1 and P_4 proposed the same gesture with a similar motivation to invoke "home screen." Another example is P_1, who placed the hand on his stomach for "menu," and said "This action [menu] made me think of the restaurant menu." These results suggest the design option of enhancing simple, low-complexity pointing movements with expressively rich connotations. In other cases, the body part referenced by the *deictic* gesture was related to the participant's specific health condition. For example, P_2 and P_4 (Spinal Cord Injury) mentioned that they chose to place their hands on the chest/heart to effect "emergency call," because of their high blood pressure complication.

We also found comments about the other Gesture-Nature categories. For example, some of the participants proposed *iconic* gestures to perform actions on imaginary objects, e.g., P_1 said that his gesture to "turn on/off the lights" was inspired by how he would pull aside a curtain, and P_5 performed a swiping gesture from head to knee mimicking how he would draw the blinds. Three participants (P_2, P_3, and P_5) held an imaginary book to access "e-books," "menu," and "photo/video," P_{11} mimicked holding an imaginary microphone to "place a call," P_8 imagined pressing the button of a photo camera to access "photo/video," P_2 pressed the buttons of an imaginary remote control to "turn on/off the TV" and "turn on/off the lights", and both P_5 and P_8 typed in mid-air on an imaginary keyboard in response to the "email" and "social media" referents. Other gestures were *symbolic* in nature, represented by

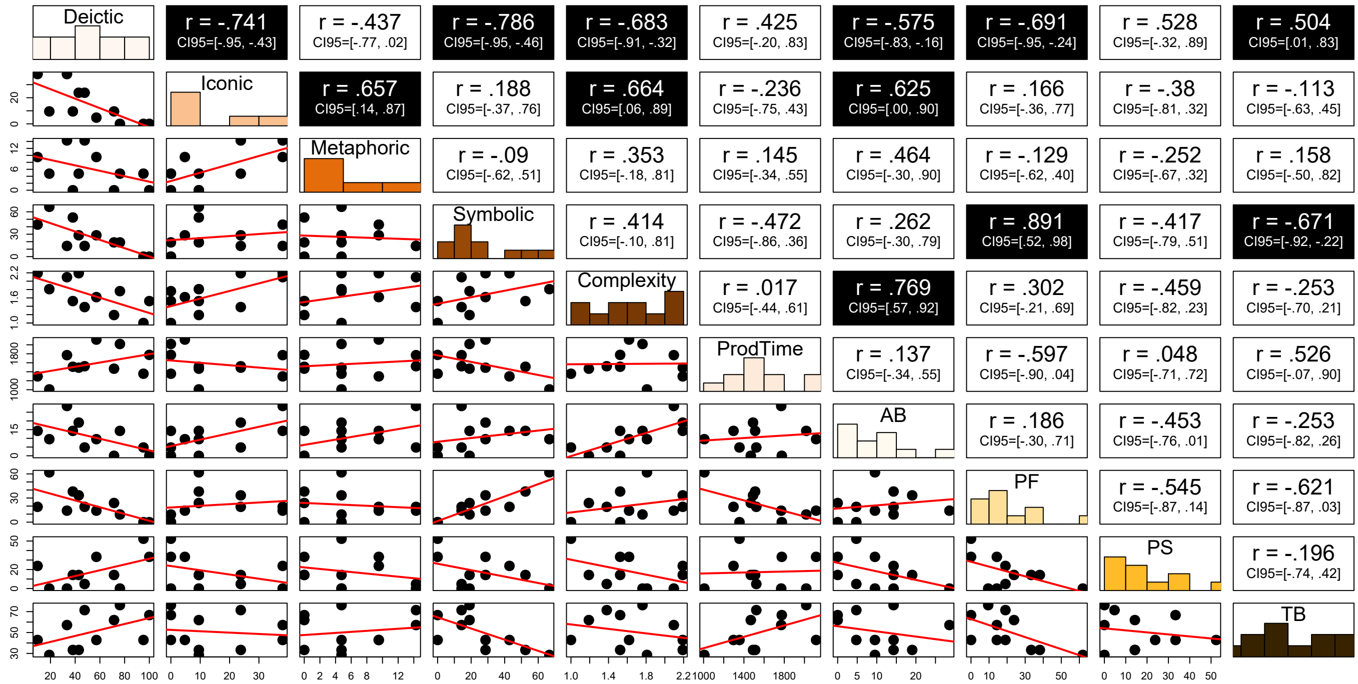

Figure 3: Relationships between the nature, complexity, motion type, and production time characteristics of user-defined gestures. *Note:* statistically significant correlations (corresponding to 95% CIs that do not include 0) are highlighted in black.

signs commonly found in graphical user interfaces. For example, P_{11} used the "thumbs-up" hand pose to access "social media" due to the similarity with the "Like" button, and P_3 said: "I am thinking about how these commands could be represented graphically. For 'turn on/off the lights,' I am thinking of a bulb, and for 'emergency call,' of the exclamation mark."

5 CONCLUSION AND FUTURE WORK

We found more preference for *deictic* gestures, mainly performed *toward the body* in the user's personal and peripersonal space, compared to *iconic* and *metaphoric* gestures and movements *away from the body* directed to the extrapersonal space. *Symbolic* gestures were simple, mostly represented by hand poses and directional swipes. Our results complement the findings of previous gesture elicitation studies [3,19,23,40] conducted with users with motor and/or mobility impairments with insights into the combined expressiveness and articulation complexity of user-defined gestures. By corroborating our results with previous reports about users with motor and/or mobility impairments preferring simple gestures [19,40] performed in easily accessible regions on and around the body [3], we suggest the existence of a potential expressivity-complexity tradeoff for accessible gesture input, to be examined more closely in future work, including for other user groups, interactive devices and systems, and application domains that use gesture-based input. Another interesting direction is understanding how the expressivity-complexity tradeoff is linked to the users' life experience and past interactions with computer systems in the context of the legacy bias phenomenon [22].

Our results also have implications for gesture input performed from the wheelchair space, for which we suggest future work opportunities. First, we found that *deictic* gestures cover a wide spectrum of the space around the user, from mid-air, in front, and to the side of the body to pointing at objects and/or locations from the *extrapersonal space* to pointing at the wheelchair in the *peripersonal space,* and toward and on the body in the *personal space,* respectively. Given the low complexity of a pointing gesture, future work is recommended to compile a vocabulary of deictics that exploits this spectrum for wheelchair users and common tasks in smart environments. Second, the large preference for gestures performed *toward* vs. *away from the body* indicates an opportunity for future interesting investigations into designing gesture-based interactions with computer systems that capitalize on aspects of body image representation and body-environment interaction (i.e., here and personal vs. there and extrapersonal) for wheelchair users as well as on the malleability of the peripersonal space representation, which can integrate the wheelchair [12]. For example, adaptive user interfaces can switch among *deictic* gestures performed away from the body directed at the extrapersonal space [32], gestures on the wheelchair [6] in the peripersonal space, and gestures toward and on the body in the personal space [3], or combinations thereof [2], according to context. Third, future exploration of *metaphoric* and *iconic* gestures, for which we found less preference in the dataset analyzed in this work, is interesting in relation to *deictic* gestures, far more common, so that the low complexity of the latter would complement the rich expressivity of the former. Examples include pointing at an imaginary object [26] or pointing that bears metaphorical meaning by design [27]. Such mixed-nature gesture designs, which capitalize on the familiarity and low complexity of deictics, are possible since "pointing has the obvious function of indicating objects and events in the concrete world, but it also plays a part even where there is nothing objectively present to point at," according to McNeill [21, p. 18]. Mixed-nature gestures could also be examined for personalizing input for users with specific motor abilities in the context of user interface adaptation [11] and input modality and device personalization [25] approaches to accessibility.

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REFERENCES

[1] Reuben M. Aronson, Nadia Almutlak, and Henny Admoni. 2021. Inferring Goals with Gaze during Teleoperated Manipulation. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '21)*. IEEE, USA, 7307–7314. https://doi.org/10.1109/IROS51168.2021.9636551

[2] Yuki Asai, Yuta Ueda, Ryuichi Enomoto, Daisuke Iwai, and Kosuke Sato. 2016. ExtendedHand on Wheelchair. In *Adjunct Proceedings of the 29th Annual ACM Symposium on User Interface Software and Technology (UIST '16 Adjunct)*. ACM, New York, NY, USA, 147–148. https://doi.org/10.1145/2984751.2985738

[3] Laura-Bianca Bilius, Ovidiu-Ciprian Ungurean, and Radu-Daniel Vatavu. 2023. Understanding Wheelchair Users' Preferences for On-Body, In-Air, and On-Wheelchair Gestures. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3544548.3580929

[4] Xiang Cao and Shumin Zhai. 2007. Modeling Human Performance of Pen Stroke Gestures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '07)*. ACM, New York, NY, USA, 1495–1504. https://doi.org/10.1145/1240624.1240850

[5] Baptiste Caramiaux, Nicola Montecchio, Atau Tanaka, and Frédéric Bevilacqua. 2014. Adaptive Gesture Recognition with Variation Estimation for Interactive Systems. *ACM Trans. Interact. Intell. Syst.* 4, 4, Article 18 (2014), 34 pages. https://doi.org/10.1145/2643204

[6] Patrick Carrington, Jian-Ming Chang, Kevin Chang, Catherine Hornback, Amy Hurst, and Shaun K. Kane. 2016. The Gest-Rest Family: Exploring Input Possibilities for Wheelchair Armrests. *ACM Trans. Accessible Computing* 8, 3, Article 12 (2016), 24 pages. https://doi.org/10.1145/2873062

[7] Patrick Carrington, Amy Hurst, and Shaun K. Kane. 2013. How Power Wheelchair Users Choose Computing Devices. In *Proceedings of the 15th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '13)*. ACM, New York, NY, USA, Article 52, 2 pages. https://doi.org/10.1145/2513383.2513426

[8] Patrick Carrington, Amy Hurst, and Shaun K. Kane. 2014. Wearables and Chairables: Inclusive Design of Mobile Input and Output Techniques for Power Wheelchair Users. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 3103–3112. https://doi.org/10.1145/2556288.2557237

[9] Chris Creed and Russell Beale. 2014. Enhancing Multi-Touch Table Accessibility for Wheelchair Users. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. ACM, New York, NY, USA, 255–256. https://doi.org/10.1145/2661334.2661388

[10] Leah Findlater, Alex Jansen, Kristen Shinohara, Morgan Dixon, Peter Kamb, Joshua Rakita, and Jacob O. Wobbrock. 2010. Enhanced Area Cursors: Reducing Fine Pointing Demands for People with Motor Impairments. In *Proceedings of the 23nd Annual ACM Symposium on User Interface Software and Technology (UIST '10)*. ACM, New York, NY, USA, 153–162. https://doi.org/10.1145/1866029.1866055

[11] Krzysztof Z. Gajos, Jacob O. Wobbrock, and Daniel S. Weld. 2007. Automatically Generating User Interfaces Adapted to Users' Motor and Vision Capabilities. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology (UIST '07)*. ACM, New York, NY, USA, 231–240. https://doi.org/10.1145/1294211.1294253

[12] Giulia Galli, Jean-Paul Noel, Elisa Canzoneri, Olaf Blanke, and Andrea Serino. 2015. The Wheelchair as a Full-Body Tool Extending the Peripersonal Space. *Frontiers in Psychology* 6 (2015), 639:1–639:11. https://doi.org/10.3389/fpsyg.2015.00639

[13] Kathrin Gerling, Patrick Dickinson, Kieran Hicks, Liam Mason, Adalberto L. Simeone, and Katta Spiel. 2020. Virtual Reality Games for People Using Wheelchairs. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '20)*. ACM, New York, NY, USA, 1–11. https://doi.org/10.1145/3313831.3376265

[14] Kilem Li Gwet. 2010. Computing Inter-Rater Reliability and Its Variance in the Presence of High Agreement. *Brit. J. Math. Statist. Psych.* 61 (2010), 29–48. https://doi.org/10.1348/000711006X126600

[15] Max Hildebrand, Frederik Bonde, Rasmus Vedel Nonboe Kobborg, Christian Andersen, Andreas Flem Norman, Mikkel Thøgersen, Stefan Hein Bengtson, Strahinja Dosen, and Lotte N. S. Andreasen Struijk. 2019. Semi-Autonomous Tongue Control of an Assistive Robotic Arm for Individuals with Quadriplegia. In *Proceedings of the 16th IEEE International Conference on Rehabilitation Robotics (ICORR '19)*. IEEE, USA, 157–162. https://doi.org/10.1109/ICORR.2019.8779457

[16] Ananda Sankar Kundu, Oishee Mazumder, Prasanna Kumar Lenka, and Subhasis Bhaumik. 2018. Hand Gesture Recognition Based Omnidirectional Wheelchair Control Using IMU and EMG Sensors. *J. Intell. Robotics Syst.* 91, 3–4 (sep 2018), 529–541. https://doi.org/10.1007/s10846-017-0725-0

[17] Mohammed Kutbi, Xiaoxue Du, Yizhe Chang, Bo Sun, Nikolaos Agadakos, Haoxiang Li, Gang Hua, and Philippos Mordohai. 2020. Usability Studies of an Egocentric Vision-Based Robotic Wheelchair. *J. Hum.-Robot Interact.* 10, 1, Article 4 (jul 2020), 23 pages. https://doi.org/10.1145/3399434

[18] Luis A. Leiva, Daniel Martín-Albo, Réjean Plamondon, and Radu-Daniel Vatavu. 2018. KeyTime: Super-Accurate Prediction of Stroke Gesture Production Times. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 239, 12 pages. https://doi.org/10.1145/3173574.3173813

[19] Meethu Malu, Pramod Chundury, and Leah Findlater. 2018. Exploring Accessible Smartwatch Interactions for People with Upper Body Motor Impairments. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 488, 12 pages. https://doi.org/10.1145/3173574.3174062

[20] Meethu Malu and Leah Findlater. 2015. Personalized, Wearable Control of a Head-Mounted Display for Users with Upper Body Motor Impairments. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 221–230. https://doi.org/10.1145/2702123.2702188

[21] David McNeill. 1992. *Hand and Mind: What Gestures Reveal About Thought*. Vol. 27. University of Chicago Press, Chicago. https://psycnet.apa.org/record/1992-98214-000

[22] Meredith Ringel Morris, Andreea Danielescu, Steven Drucker, Danyel Fisher, Bongshin Lee, m. c. schraefel, and Jacob O. Wobbrock. 2014. Reducing Legacy Bias in Gesture Elicitation Studies. *Interactions* 21, 3 (may 2014), 40–45. https://doi.org/10.1145/2591689

[23] David M. Roy, Marilyn Panayi, Roman Erenshteyn, Richard Foulds, and Robert Fawcus. 1994. Gestural Human-Machine Interaction for People with Severe Speech and Motor Impairment Due to Cerebral Palsy. In *Conference Companion on Human Factors in Computing Systems (CHI '94)*. ACM, New York, NY, USA, 313–314. https://doi.org/10.1145/259963.260375

[24] Quentin Roy, Sylvain Malacria, Yves Guiard, Eric Lecolinet, and James Eagan. 2013. Augmented Letters: Mnemonic Gesture-Based Shortcuts. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 2325–2328. https://doi.org/10.1145/2470654.2481321

[25] Ovidiu-Andrei Schipor, Laura-Bianca Bilius, and Radu-Daniel Vatavu. 2022. WearSkill: Personalized and Interchangeable Input with Wearables for Users with Motor Impairments. In *Proceedings of the 19th International Web for All Conference (W4A '22)*. ACM, New York, NY, USA, Article 10, 5 pages. https://doi.org/10.1145/3493612.3520455

[26] Ovidiu-Andrei Schipor and Radu-Daniel Vatavu. 2018. Invisible, Inaudible, and Impalpable: Users' Preferences and Memory Performance for Digital Content in Thin Air. *IEEE Pervasive Computing* 17, 04 (2018), 76–85. https://doi.org/10.1109/MPRV.2018.2873856

[27] Zhida Sun, Sitong Wang, Chengzhong Liu, and Xiaojuan Ma. 2022. Metaphoraction: Support Gesture-Based Interaction Design with Metaphorical Meanings. *ACM Trans. Comput.-Hum. Interact.* 29, 5, Article 45 (oct 2022), 33 pages. https://doi.org/10.1145/3511892

[28] Katherine M. Tsui, Dae-Jin Kim, Aman Behal, David Kontak, and Holly A. Yanco. 2011. "I Want That": Human-in-the-Loop Control of a Wheelchair-Mounted Robotic Arm. *Appl. Bionics Biomechanics* 8, 1 (jan 2011), 127–147.

[29] Ovidiu-Ciprian Ungurean and Radu-Daniel Vatavu. 2021. Coping, Hacking, and DIY: Reframing the Accessibility of Interactions with Television for People with Motor Impairments. In *Proceedings of the ACM International Conference on Interactive Media Experiences (IMX '21)*. ACM, New York, NY, USA, 37–49. https://doi.org/10.1145/3452918.3458802

[30] Ovidiu-Ciprian Ungurean and Radu-Daniel Vatavu. 2022. "I Gave up Wearing Rings:" Insights on the Perceptions and Preferences of Wheelchair Users for Interactions With Wearables. *IEEE Pervasive Computing* 21, 3 (2022), 92–101. https://doi.org/10.1109/MPRV.2022.3155952

[31] Radu-Daniel Vatavu and Ovidiu-Ciprian Ungurean. 2022. Understanding Gesture Input Articulation with Upper-Body Wearables for Users with Upper-Body Motor Impairments. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '22)*. ACM, New York, NY, USA, Article 2, 16 pages. https://doi.org/10.1145/3491102.3501964

[32] Radu-Daniel Vatavu, Ovidiu-Ciprian Ungurean, and Laura-Bianca Bilius. 2022. Interactive Public Displays and Wheelchair Users: Between Direct, Personal and

Indirect, Assisted Interaction. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. ACM, New York, NY, USA, Article 45, 17 pages. https://doi.org/10.1145/3526113.3545662

[33] Radu-Daniel Vatavu, Daniel Vogel, Géry Casiez, and Laurent Grisoni. 2011. Estimating the Perceived Difficulty of Pen Gestures. In *Proceedings of the 13th IFIP TC 13 International Conference on Human-Computer Interaction (INTERACT'11)*. Springer-Verlag, Berlin, Heidelberg, 89–106.

[34] Radu-Daniel Vatavu and Jacob O. Wobbrock. 2022. Clarifying Agreement Calculations and Analysis for End-User Elicitation Studies. *ACM Trans. Comput.-Hum. Interact.* 29, 1, Article 5 (jan 2022), 70 pages. https://doi.org/10.1145/3476101

[35] Santiago Villarreal-Narvaez, Jean Vanderdonckt, Radu-Daniel Vatavu, and Jacob O. Wobbrock. 2020. A Systematic Review of Gesture Elicitation Studies: What Can We Learn from 216 Studies?. In *Proceedings of the ACM Designing Interactive Systems Conference*. ACM, New York, NY, USA, 855–872. https://doi.org/10.1145/3357236.3395511

[36] Jacob O. Wobbrock, Htet Htet Aung, Brandon Rothrock, and Brad A. Myers. 2005. Maximizing the Guessability of Symbolic Input. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems (CHI EA '05)*. ACM, New York, NY, USA, 1869–1872. https://doi.org/10.1145/1056808.1057043

[37] Jacob O. Wobbrock, Krzysztof Z. Gajos, Shaun K. Kane, and Gregg C. Vanderheiden. 2018. Ability-Based Design. *Commun. ACM* 61, 6 (may 2018), 62–71. https://doi.org/10.1145/3148051

[38] Jacob O. Wobbrock, Meredith Ringel Morris, and Andrew D. Wilson. 2009. User-Defined Gestures for Surface Computing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 1083–1092. https://doi.org/10.1145/1518701.1518866

[39] Jacob O. Wobbrock, Brad A. Myers, Htet Htet Aung, and Edmund F. LoPresti. 2003. Text Entry from Power Wheelchairs: Edgewrite for Joysticks and Touchpads. In *Proceedings of the 6th International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '04)*. ACM, New York, NY, USA, 110–117. https://doi.org/10.1145/1028630.1028650

[40] Xuan Zhao, Mingming Fan, and Teng Han. 2022. "I Don't Want People to Look At Me Differently": Designing User-Defined Above-the-Neck Gestures for People with Upper Body Motor Impairments. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '22)*. ACM, New York, NY, USA, Article 1, 15 pages. https://doi.org/10.1145/3491102.3517552