Empowering Accessible Gesture Input Design with Gesture-A11Y

Mihail Terenti
MintViz Lab, MANSiD Research Center
Ştefan cel Mare University of Suceava
Suceava, Romania
mihail.terenti@usm.ro

Laura-Bianca Bilius
MintViz Lab, MANSiD Research Center
Ştefan cel Mare University of Suceava
Suceava, Romania
laura.bilius@usm.ro

Ovidiu-Ciprian Ungurean
MintViz Lab, MANSiD Research Center
Ştefan cel Mare University of Suceava
Suceava, Romania
ungurean.ovidiu@gmail.com

Radu-Daniel Vatavu
MintViz Lab, MANSiD Research Center
Ştefan cel Mare University of Suceava
Suceava, Romania
radu.vatavu@usm.ro

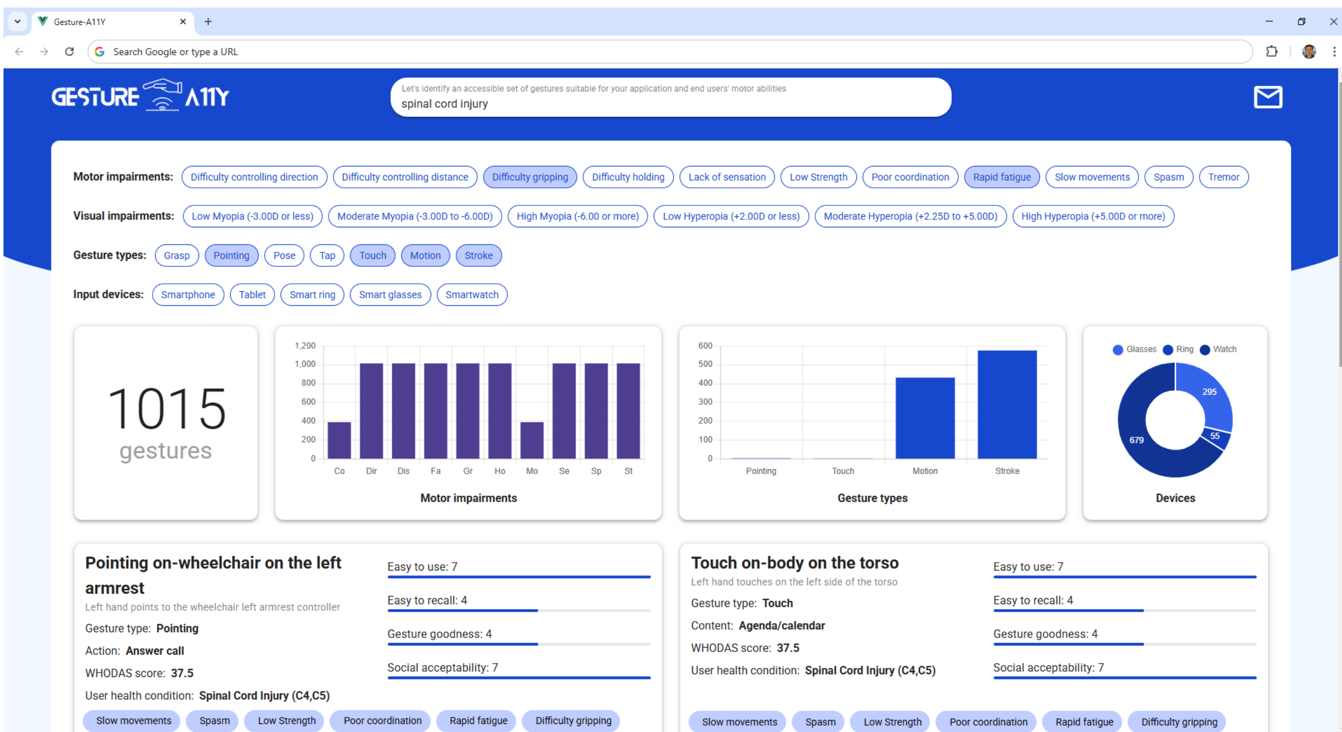

Figure 1: Gesture-A11Y is a web-based tool and database meant to assist researchers and practitioners in identifying suitable gesture input for users with various abilities. The search features, illustrated in this screenshot, utilize *keywords, impairment descriptions, gesture types,* and *input devices* to navigate a database of over 22,000 records involving computational recordings of 2D touchscreen and 3D mid-air gestures, mappings between gestures and system functions, and end-user self-reported preferences for gesture input. In this example, 1015 gesture records were identified when searching for "spinal cord injury" and filtering on "difficulty gripping" and "rapid fatigue" symptoms and "pointing," "touch," "motion," and "stroke" gesture types.

Abstract

Understanding end-user performance with gesture input is essential for designing intuitive and effective interactions. Unfortunately, open gesture datasets are scarce, in particular those addressing users with impairments, which hinders advancements in accessible and inclusive user interface design for devices and applications featuring gesture interactions. To address this, we introduce Gesture-A11Y, a web-based tool with a large database aimed to help identify gestures

W4A '25, Sydney, NSW, Australia

ACM ISBN 979-8-4007-1882-3/25/04
https://doi.org/10.1145/3744257.3744267

aligning with users' abilities and preferences. Gesture-A11Y offers access to over 22,000 records of *touchscreen, mid-air, on-body,* and *on-wheelchair gestures* performed by users with various visual and/or motor abilities, along with their preferences and perceptions of gesture input across different mobile and wearable devices.

CCS Concepts

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

Keywords

Gesture input, web-based tool, accessibility, impairments, visual impairments, gesture set design, touch, motion, mid-air

ACM Reference Format:
Mihail Terenti, Laura-Bianca Bilius, Ovidiu-Ciprian Ungurean, and Radu-Daniel Vatavu. 2025. Empowering Accessible Gesture Input Design with Gesture-A11Y. In *W4A '25: Proceedings of the 22nd International Web for All Conference (W4A '25), April 28–29, 2025, Sydney, NSW, Australia.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3744257.3744267

1 Introduction

Open-access datasets are notoriously scarce in the field of Human-Computer Interaction, hindering replication of scientific findings, consolidation of design knowledge, and development of new interactive systems. When it comes to users experiencing disabilities, open data is even more challenging to find [17,21,25], particularly for gesture interaction despite the fact that prevalent mobile devices rely primarily on gesture input. However, access to data representative of users' gesture articulations and preferences is crucial for implementing suitable interaction techniques [22] and robust gesture recognition algorithms [33]. For example, Figure 2 shows touchscreen gestures produced on a mobile device by a user without visual impairments (left) and a user with low vision (right), revealing differences that need to be accommodated in the interface for effective user performance and a rewarding experience.

In this context, advancing accessible gesture-based interaction with computer systems is severely constrained, as researchers lack datasets to replicate prior findings or to compare their own results, while practitioners lack critical design information needed to inform their interactive prototypes. Given that prevalent mobile devices, such as smartphones, implicitly rely on gesture input, gesture input accessibility plays a significant role in determining overall mobile accessibility and, ultimately, can negatively impact access to digital resources and services and, in turn, affect employability [14,28]. To address these aspects, we introduce Gesture-A11Y, a web-based searchable database and tool currently featuring 22,854 gesture records collected from users with visual and/or motor impairments. Gesture-A11Y is the only tool of its kind, providing access to an unprecedented large dataset to support accessible gesture input design. We also present practical applications of Gesture-A11Y, showing how its resources can be readily used to advance the development of user interfaces featuring accessible gesture input.

2 Related Work

The accessibility community has focused on understanding the challenges with interactive computer systems encountered by users

Figure 2: Touchscreen gestures for the "five-point star" symbol produced by a user without impairments (left) and a user with congenital nystagmus and high myopia (right). Ten articulations are shown superimposed. Note the higher variation in geometry and structure in the latter, which requires appropriate recognition and interaction techniques.

experiencing disabilities, leading to insightful advancements in interface design, input devices, and interaction techniques [4–6,9,15,23,29,32]. For example, Plaumann et al. [23] introduced a method for correcting touch input inaccuracies caused by hand tremors by analyzing device motion. Trivedi et al. [29] proposed a system for controlling wheelchairs using head movements captured by a camera. Li et al. [15] developed a touch-gesture text input technique that enables Braille typing. Vahdani et al. [32] introduced iSense, a wearable featuring obstacle detection, spatial navigation, and object recognition. Penuela et al. [9] designed a haptic glove enabling object description in virtual environments through hand gestures.

Gesture interaction research has covered both the development of new input devices and analyses of user preferences [2,8,19,20]. Malu et al. [19] examined the accessibility of smartwatch gestures, such as taps, swipes, and letter scribbling for text input, Buzzi et al. [2] reported on the characteristics of touch gestures articulated by users with visual impairments, and Kane and Wobbrock [13] examined gestures defined by blind users on a mobile device. Malu et al. [20] designed an input technique for users with motor impairments involving touchpads attached to their body or wheelchair.

Despite innovations in accessible gesture input, open data remains scarce. Unfortunately, this impedes inclusive practices, limiting current efforts in developing more accessible interactions.

3 Gesture-A11Y

We present Gesture-A11Y, our web-based tool and database for informing accessible gesture input for users experiencing disabilities.

3.1 Design and Development

We adopted the following design principles for Gesture-A11Y emphasizing (i) open access to scientific knowledge and design information about gesture input performed by users with impairments and (ii) open-source technology. In drawing out these principles, we relied on the three elements of the context of use [3] for interactive computer systems—*users, platforms,* and *environments*—as follows.

3.1.1 Users with diverse abilities. Gesture-A11Y is intended as a hub for open access to gesture input records representative of users' gesture articulation abilities and preferences. To this end, it features end-user demographics, such as self-reported motor symptoms for users with motor impairments (e.g., rapid fatigue or tremor), visual

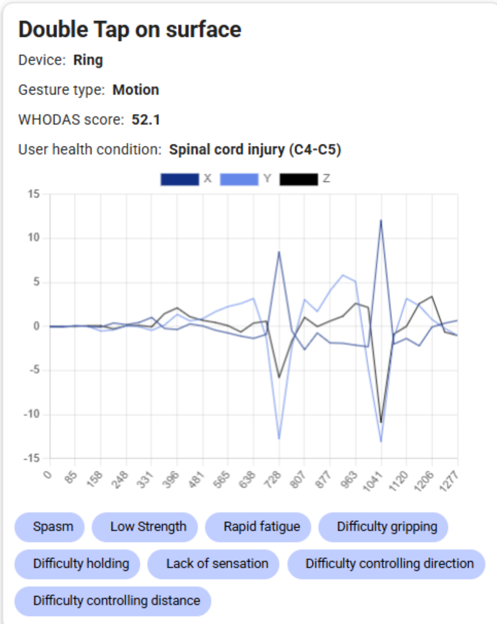

Figure 3: Example of a gesture record in Gesture-A11Y with a computational representation of 3-axis linear acceleration. In this example, a user with spinal cord injury, reporting rapid fatigue, among other impairments, performed a double tap on a nearby surface, captured by an electronic ring.

acuity levels for users with visual impairments (e.g., the degree of refractive error in myopia and hyperopia), medical diagnoses (e.g., macular choroiditis) and causes of impairment (e.g., spinal cord injury), alongside standardized disability assessments (e.g., WHODAS [37] scores through the World Health Organization Disability Assessment Schedule 2.0); see Figure 3 for examples of end-user information in our gesture records.

3.1.2 Diverse types of devices and gestures. Gesture-A11Y provides access to gestures performed using mobile and wearable devices, such as smartphones and smartwatches, as well as gestures involving different support surfaces, such as the wheelchair's armrest or the user's body. These include touch input in the form of swipes and symbolic strokes [33–35], mid-air [1,35], on-body [1], and on-wheelchair gestures [1]. Most of the records are provided in a computational form (e.g., stroke gestures produced on touchscreens are represented as series of (x, y) coordinates and motion gestures produced in mid-air as series of (x, y, z) linear accelerations; see Figure 3 for an example), while others represent end-user evaluations of specific gesture types (e.g., through ease-of-use and social acceptability ratings, as illustrated in Figure 1).

3.1.3 Diverse environments. Gesture input and preferences available in Gesture-A11Y were collected in both private [1,30] and public [33,34] settings to ensure ecological validity and capture diverse interaction patterns.

In developing Gesture-A11Y, we adopted open-source web technologies to ensure broad access to our database and user interface from virtually any platform or device with a web browser. We used JavaScript for the frontend with Vue.js,[1] a progressive and reactive framework that allowed us to build the interface for navigating and visualizing the gesture dataset; see Figure 1 for a screenshot. The UI implements Material Design principles[2] for modern, consistent, and easily recognizable interface elements. Furthermore, we used Golang[3] to handle backend operations, which we chose for its sophisticated concurrency model, enabling us to build a high performing system capable of efficiently processing simultaneous requests. Instead of a traditional relational database, we preferred storing gesture data in CSV and XML files, making the database simple and lightweight. For this, we employed Pandas,[4] a popular Python library for processing tabular data. Gesture records are represented through information cards, illustrated in Figures 1 and 3, which include all or part of the following information: a brief gesture description, the corresponding system function that the gesture executes, gesture type, user evaluation ratings, user demographics, and the gesture visualization from its computational form. To enable searching across this diversified set of records, we indexed them based on the following criteria (see Figure 1, top):

- *Keywords.* We implemented keyword-based search to identify gesture records through their associated descriptions, e.g., searching for "TV" returns all gestures associated with this device, while searching for "rotate" lists gestures that include rotation in their description.
- *Gesture types.* We used common gesture types to help identify specific interaction styles, such as touch, motion, stroke, pointing, etc. For example, choosing "stroke" will list gestures produced on touchscreens, such as symbols and letters on a smartphone [34] or swipes on a smartwatch [35].
- *Specific impairments.* We implemented a search facility based on specific impairments, such as spasm or tremor for users with motor impairments [7], and low, moderate, and high myopia and hyperopia for users with low vision [33].
- *Device type.* The user interface enables filtering gestures according to the target device, such as the smartwatch.

3.2 Content

Gesture-A11Y features access to a total of 22,854 gesture records to date, collected from 122 users with various visual and/or motor impairments. These include gestures represented in computational form, mappings between user-defined gestures and system functions, and user preference evaluations of gestures and input devices.

3.2.1 Stroke gestures on mobile devices. A stroke gesture [18] is a 2D path performed on a touchscreen, such as a directional swipe, a letter, or a symbol. Stroke gestures allow direct function invocation, such as drawing the letter "C" for quick access to phone contacts [16]. Gesture-A11Y contains a total of 4,662 stroke gestures collected from 35 people with motor impairments [34]: directional swipes, letters (Roman letters M, X, R and Greek letters alpha and pi), symbols (checkmark, energy, Euro, paper clip), and geometric shapes (heart, six-point star, and spiral). It also includes 3,313 stroke

[1]https://vuejs.org
[2]https://m3.material.io
[3]https://go.dev
[4]https://pandas.pydata.org

gestures collected from 27 people with visual impairments [33]: letters (A, M, R, S), symbols (arrow right, stick figure, question mark, sol key), and geometric shapes (spiral, square, star, and circle). These gestures are represented as series of (x, y) screen coordinates.

3.2.2 Stroke gestures on wearables. Entering gestures on wearables is challenging due to the small size of the integrated touchscreen. Gesture-A11Y contains a total of 7,290 stroke gestures collected from 14 people with motor impairments [35]: directional swipes, letters (A, M, X), symbols (checkmark, asterisk, zigzag) and geometric shapes (circle, heart, six-point star, square). These were performed on a touchscreen worn at the wrist as a smartwatch, on the index finger as a ring, and attached to the temple of a pair of glasses.

3.2.3 Mid-air motion gestures. A motion gesture is a 3D path performed in mid-air, such as placing the phone to the ear to initiate a call [24] or positioning the hands in a specific pose in front of the body [10], and come in a variety of forms [11]. Gesture-A11Y contains 3,809 gestures from 14 participants with motor impairments [35], including wrist movements (mid-air hand tap, double tap, circle, shake, outward and inward motion), finger movements (finger tap, double tap, circle, scratch surface, thumb-to-index pinch, and slide the index finger on the thumb), and head movements (head tap, double tap, circle, rotate, lean forward, tilt to shoulder). These gestures are available as series of (x, y, z) linear accelerations.

3.2.4 User-defined mappings between gestures and system functions. Gesture elicitation studies [36] are designed to provide insights into users' preferences for gesture input and help establish consensus gesture sets across users. Gesture-A11Y contains 231 user-defined gestures collected from 11 people with motor impairments [1], including hand gestures performed on the body, in mid-air, and on the wheelchair. It also includes 924 associated self-reported ratings of ease of execution, recall, goodness of fit, and social acceptability.

3.2.5 User preference for gesture input. Lastly, Gesture-A11Y contains 2,625 ratings collected from 21 people with motor impairments [31] reflecting their perceptions of current wearables—fitness trackers, smartwatches, smart glasses, earbuds, and rings—across desirability, ease of access, ease of wear, ease of use, fun, unwanted attention, input modality, and social acceptability dimensions. These preferences are provided as ratings on a 5-point Likert scale.

3.3 Use Case Examples

We illustrate how Gesture-A11Y can support advancements in accessible gesture input design through several use cases.

3.3.1 Gesture set identification with Gesture-A11Y. Consider a practitioner designing an accessible smart TV interface for users with upper-body motor impairments. Since conventional remote controls can be difficult to grasp, hold steadily, and operate [30], the practitioner decides for a bare-hand interface. To identify suitable gestures, they access Gesture-A11Y and perform a keyword-based search for "TV." This search returns 11 relevant gestures, from which the practitioner selects the following: *touching the right thigh*, proposed by a person with spinal cord injury experiencing difficulty holding objects—a simple, low effort gesture rated highly for ease of use; *pointing in front of the body*, suggested by a person with multiple sclerosis and rated highest for ease of recall; and *performing a hand pose in mid-air*, recommended by a person with Parkinson's, who experiences slow movements and difficulty controlling direction. These insights into users' gesture preferences across various motor impairments, available in just a matter of seconds, provide a good foundation for the design process. The practitioner can now begin considering suitable sensing and recognition technologies.

3.3.2 Gesture recognition evaluation. Consider a researcher developing a new recognition algorithm for stroke gestures performed by users with visual impairments on touchscreens. They access the 2D paths from Gesture-A11Y and run initial analyses to understand the characteristics of these gestures, finding that production times average 3.8s (SD=3.9) and path lengths 24.6cm (SD=14.5). These insights suggest that aligning gesture paths, such as via Dynamic Time Warping (DTW), a popular gesture dissimilarity function [27], may be necessary to account for variations in length and time. The researcher also finds that the Nearest-Neighbor approach with DTW yields an average accuracy of 85.4%, increasing from 61.2% with training data from just one participant and one example per gesture type to 92.8% when using training data from 10 participants and 10 examples.[5] This information provides a solid baseline condition against which to evaluate the new recognition algorithm.

3.3.3 Future development and use cases. We envision several future work opportunities for Gesture-A11Y, enabling more use cases. First, we aim to establish it as a living hub where researchers and practitioners share their data. Second, we believe that AI models could be trained on our large database for generative interaction design [26]; for example, this could lead to better mappings between users' abilities and gesture commands (our first use case above) and more accurate recognizers (our second use case). Third, we would like to integrate Gesture-A11Y with design tools, such as via Figma plugins,[6] to streamline UI development. This will enable use cases where UI design and gesture set design are combined and tested within the same workflow; for example, when a new UI element, such as a navigation list, is added to the interface, suitable gestures could be automatically retrieved from Gesture-A11Y and suggested to the designer to ensure the interface's accessibility.

4 Conclusion

We introduced Gesture-A11Y, the first hub for gesture input and users with impairments, providing access to over 22,000 records, a database of unprecedented size in accessibility research and practice, especially given the scarcity of such resources. Gesture-A11Y comes with an open-source license for unrestricted access to its database to foster democratization of accessible gesture input design, including Do-It-Yourself practices in assistive technology [12]. In the context where the vast majority of interactions with mobile devices rely implicitly on gesture input, gesture accessibility plays a key role in overall mobile interaction accessibility, and improving it can contribute to more inclusive employment by ensuring access to digital resources and services through mobile devices. We look forward to advancements in gesture input techniques made possible by unprecedented access to resources in inclusive gesture input.

[5] Actual measurements from 3,313 stroke gestures produced by 27 people with visual impairments [33], readily available through Gesture-A11Y.
[6] https://www.figma.com/plugin-docs

Acknowledgments

This work was supported by a grant of the Ministry of Education and Research, CCCDI-UEFISCDI, project number PN-IV-P7-7.1-PTE-2024-0434, within PNCDI IV. The gesture sets made available through Gesture-A11Y were collected in the projects PN-II-RU-TE-2014-4-1187, PN-III-P2-2.1-PED-2016-0688, PN-III-P2-2.1-PED-2019-0352, and PN-III-P4-ID-PCE-2020-0434 within PNCDI III.

References

[1] 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, Article 78, 16 pages. doi:10.1145/3544548.3580929

[2] Maria Claudia Buzzi, Marina Buzzi, Barbara Leporini, and Amaury Trujillo. 2015. Exploring Visually Impaired People's Gesture Preferences for Smartphones. In *Proceedings of the 11th Biannual Conference of the Italian SIGCHI Chapter (CHItaly '15)*. ACM, New York, NY, USA, 94–101. https://doi.org/10.1145/2808435.2808448

[3] Gaëlle Calvary, Joëlle Coutaz, David Thevenin, Quentin Limbourg, Laurent Bouillon, and Jean Vanderdonckt. 2003. A Unifying Reference Framework for multi-target user interfaces. *Interacting with Computers* 15, 3 (2003), 289–308. doi:10.1016/S0953-5438(03)00010-9

[4] 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. Access. Comput.* 8, 3, Article 12 (April 2016), 24 pages. https://doi.org/10.1145/2873062

[5] Patrick Carrington, Amy Hurst, and Shaun K. Kane. 2014. The Gest-Rest: A pressure-sensitive chairable input pad for power wheelchair armrests. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. ACM, New York, NY, USA, 201–208. https://doi.org/10.1145/2661334.2661374

[6] 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

[7] 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. doi:10.1145/1866029.1866055

[8] Paul D. S. Fink, Velin Dimitrov, Hiroshi Yasuda, Tiffany L. Chen, Richard R. Corey, Nicholas A. Giudice, and Emily S. Sumner. 2023. Autonomous is Not Enough: Designing Multisensory Mid-Air Gestures for Vehicle Interactions Among People with Visual Impairments. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, Article 74, 13 pages. https://doi.org/10.1145/3544548.3580762

[9] Ricardo E. Gonzalez Penuela, Wren Poremba, Christina Trice, and Shiri Azenkot. 2022. Hands-On: Using Gestures to Control Descriptions of a Virtual Environment for People with Visual Impairments. In *Adjunct Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. ACM, New York, NY, USA, Article 84, 4 pages. https://doi.org/10.1145/3526114.3558669

[10] Celeste Groenewald, Craig Anslow, Junayed Islam, Chris Rooney, Peter Passmore, and William Wong. 2016. Understanding 3D mid-air hand gestures with interactive surfaces and displays: a systematic literature review. In *Proceedings of the 30th International BCS Human Computer Interaction Conference: Fusion! (HCI '16)*. BCS Learning & Development Ltd., Swindon, GBR, Article 43, 13 pages. doi:10.14236/ewic/HCI2016.43

[11] Masoumehsadat Hosseini, Tjado Ihmels, Ziqian Chen, Marion Koelle, Heiko Müller, and Susanne Boll. 2023. Towards a Consensus Gesture Set: A Survey of Mid-Air Gestures in HCI for Maximized Agreement Across Domains. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, Article 311, 24 pages. doi:10.1145/3544548.3581420

[12] Amy Hurst. 2018. Making "Making" Accessible. In *Proceedings of the 15th International Web for All Conference (W4A '18)*. ACM, New York, NY, USA, Article 1, 1 pages. doi:10.1145/3192714.3192715

[13] Shaun K. Kane, Jacob O. Wobbrock, and Richard E. Ladner. 2011. Usable gestures for blind people: understanding preference and performance. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 413–422. doi:10.1145/1978942.1979001

[14] Douglas Kruse, Lisa Schur, Hazel-Anne Johnson-Marcus, Lauren Gilbert, Antonio Di Lallo, Weibo Gao, and Hao Su. 2024. Assistive Technology's Potential to Improve Employment of People with Disabilities. *Journal of Occupational Rehabilitation* 34, 2 (2024), 299–315. doi:10.1007/s10926-023-10164-w

[15] Mingzhe Li, Mingming Fan, and Khai N. Truong. 2017. BrailleSketch: A Gesture-based Text Input Method for People with Visual Impairments. In *Proceedings of the 19th Int. ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '17)*. ACM, New York, NY, USA, 12–21. https://doi.org/10.1145/3132525.3132528

[16] Yang Li. 2010. Gesture search: a tool for fast mobile data access. In *Proceedings of the 23nd Annual ACM Symposium on User Interface Software and Technology (UIST '10)*. ACM, New York, NY, USA, 87–96. doi:10.1145/1866029.1866044

[17] Kelly Mack, Emma McDonnell, Dhruv Jain, Lucy Lu Wang, Jon E. Froehlich, and Leah Findlater. 2021. What Do We Mean by "Accessibility Research"? A Literature Survey of Accessibility Papers in CHI and ASSETS from 1994 to 2019. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '21)*. ACM, New York, NY, USA, Article 371, 18 pages. doi:10.1145/3411764.3445412

[18] Nathan Magrofuoco, Paolo Roselli, and Jean Vanderdonckt. 2021. Two-dimensional Stroke Gesture Recognition: A Survey. *ACM Comput. Surv.* 54, 7, Article 155 (July 2021), 36 pages. doi:10.1145/3465400

[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, 1–12. https://doi.org/10.1145/3173574.3174062

[20] Meethu Malu, Pramod Chundury, and Leah Findlater. 2019. Motor Accessibility of Smartwatch Touch and Bezel Input. In *Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '19)*. ACM, New York, NY, USA, 563–565. https://doi.org/10.1145/3308561.3354638

[21] Tamanna Motahar and Jason Wiese. 2022. A Review of Personal Informatics Research for People with Motor Disabilities. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 6, 2, Article 66 (July 2022), 31 pages. doi:10.1145/3534614

[22] Martez E. Mott, Radu-Daniel Vatavu, Shaun K. Kane, and Jacob O. Wobbrock. 2016. Smart Touch: Improving Touch Accuracy for People with Motor Impairments with Template Matching. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 1934–1946. https://doi.org/10.1145/2858036.2858390

[23] Katrin Plaumann, Milos Babic, Tobias Drey, Witali Hepting, Daniel Stooss, and Enrico Rukzio. 2018. Improving Input Accuracy on Smartphones for Persons who are Affected by Tremor using Motion Sensors. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 156 (Jan. 2018), 30 pages. https://doi.org/10.1145/3161169

[24] Jaime Ruiz, Yang Li, and Edward Lank. 2011. User-Defined Motion Gestures for Mobile Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 197–206. doi:10.1145/1978942.1978971

[25] Alexandru-Ionuţ Siean and Radu-Daniel Vatavu. 2021. Wearable Interactions for Users with Motor Impairments: Systematic Review, Inventory, and Research Implications. In *Proceedings of the 23rd International ACM SIGACCESS Conference on Computers and Accessibility (ASSETS '21)*. ACM, New York, NY, USA, Article 7, 15 pages. doi:10.1145/3441852.3471212

[26] Macy Takaffoli, Sijia Li, and Ville Mäkelä. 2024. Generative AI in User Experience Design and Research: How Do UX Practitioners, Teams, and Companies Use GenAI in Industry?. In *Proceedings of the ACM Designing Interactive Systems Conference*. ACM, New York, NY, USA, 1579–1593. doi:10.1145/3643834.3660720

[27] Eugene M. Taranta II, Amirreza Samiei, Mehran Maghoumi, Pooya Khaloo, Corey R. Pittman, and Joseph J. LaViola Jr. 2017. Jackknife: A Reliable Recognizer with Few Samples and Many Modalities. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 5850–5861. doi:10.1145/3025453.3026002

[28] Shyamli Thakur, Ashish Joshi, and Ashoo Grover. 2024. Mobile Phones as Assistive Technologies: Gaps and Opportunities. In *Advances in Assistive Technologies*, R. Singh and V.C. Verma (Eds.). Springer, Singapore, 33–47. doi:10.1007/978-981-97-5726-8_4

[29] Amit Ranjan Trivedi, Abhash Kumar Singh, Sundara Tejaswi Digumarti, Deepak Fulwani, and Swagat Kumar. 2013. Design and Implementation of a Smart Wheelchair. In *Proceedings of Conference on Advances In Robotics (AIR '13)*. ACM, New York, NY, USA, 1–6. https://doi.org/10.1145/2506095.2506140

[30] 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 2021 ACM International Conference on Interactive Media Experiences (IMX '21)*. ACM, New York, NY, USA, 37–49. doi:10.1145/3452918.3458802

[31] 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 (July 2022), 92–101. doi:10.1109/MPRV.2022.3155952

[32] Saeed Vahdani, Amirein Nazari, Ali Bokaeian, Saleh Ebrahimian, Omid Salehinia, Saleh Farsi, Elham Armin, Maryam Saeedi Fard, Mohammad Sadegh Ahmadi, Amirmahdi Zarif Shahsavan Nejad, Seyyed Ahmad Nezami, Mohammad Mahdi Arvili, Ali Vahdani, Ahad Harati, and Ali Esmaeili. 2025. iSense: A Wearable Solution to Enhance Accessibility for Visually Impaired People. In *Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction (HRI '25)*. IEEE, USA, 1806–1809. https://dl.acm.org/doi/10.5555/3721488.3721775

[33] Radu-Daniel Vatavu, Bogdan-Florin Gheran, and Maria-Doina Schipor. 2018. The Impact of Low Vision on Touch-Gesture Articulation on Mobile Devices. *IEEE Pervasive Computing* 17, 1 (2018), 27–37. doi:10.1109/MPRV.2018.011591059

[34] Radu-Daniel Vatavu and Ovidiu-Ciprian Ungurean. 2019. Stroke-Gesture Input for People with Motor Impairments: Empirical Results & Research Roadmap. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, 1–14. doi:10.1145/3290605.3300445

[35] 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 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. ACM, New York, NY, USA, Article 2, 16 pages. doi:10.1145/3491102.3501964

[36] 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. doi:10.1145/1518701.1518866

[37] World Health Organization. 2010. Measuring Health and Disability Manual for WHO Disability Assessment Schedule WHODAS 2.0. https://www.who.int/publications/i/item/measuring-health-and-disability-manual-for-who-disability-assessment-schedule-(-whodas-2.0)