Disability and Rehabilitation: Assistive Technology

ISSN: 1748-3107 (Print) 1748-3115 (Online) Journal homepage: www.tandfonline.com/journals/iidt20

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To cite this article: Bruno Afonso, André Perrotta & Joaquim Alvarelhão (29 Jun 2026): Movement-based assistive technology for control of digital applications in severe motor impairment: a scoping review, Disability and Rehabilitation: Assistive Technology, DOI: 10.1080/17483107.2026.2693221

To link to this article: https://doi.org/10.1080/17483107.2026.2693221

Published online: 29 Jun 2026.

DISABILITY AND REHABILITATION: ASSISTIVE TECHNOLOGY
https://doi.org/10.1080/17483107.2026.2693221

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Movement-based assistive technology for control of digital applications in severe motor impairment: a scoping review

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ABSTRACT

Technological advances have enabled new ways for individuals with severe motor impairments (SMI) to interact with computer-based applications, yet standard human–computer interfaces often remain inaccessible, creating a need for assistive technologies (AT) tailored to diverse motor abilities. This scoping review aims to identify existing AT solutions that enable individuals with SMI to use residual movements for controlling digital applications, characterizing key trends and gaps. Searches were conducted in Scopus and Web of Science Core Collection for studies published between 2012 and June 2024, and data collection took place from July to December 2024. In total 49 articles were included in the review. In addition to descriptive indicators, cross-topic analyses were performed using relationship and correspondence analysis. Overall, the AT landscape for SMI users is dominated by head-based control and 2D pointer interaction for tasks such as typing and navigation. Three-quarters of the publications addressed SMI generically, without specifying underlying conditions or detailed movement profiles. Vision systems dominate, followed by electromyographic and kinematic setups. Most systems employed explicit direct mappings, with only 20% using machine learning. A quarter of systems incorporated auxiliary feedback, with haptics used in only a small minority. Despite advancements in sensor technology and signal processing, improvements are still needed in key areas: integrating multimodal input and feedback, applying machine learning to the design process, and clearly defining target motor profiles. Future research should address these gaps, exploring novel use cases beyond conventional computing tasks and expanding participation among individuals with SMI.

ARTICLE HISTORY
Received 27 February 2026
Revised 2 June 2026
Accepted 15 June 2026

KEYWORDS
Assistive technology; severe motor impairment; Human-Computer interaction; user adaptability; digital applications

IMPLICATIONS FOR REHABILITATION

- The scarcity of studies defining or targeting specific motor profiles underscores the importance of rehabilitation professionals advocating its critical importance in tailoring interventions that connect movement capabilities with clear, goal-oriented digital activities, thus fulfilling the Human Activity Assistive Technology (HAAT) model's emphasis on activity goals.
- The findings highlight a lack of studies investigating the multimodal input and feedback systems that facilitate effective interaction with digital tasks, underscoring the need for increased research in this field.
- Machine learning approaches in assistive technology design enhance adaptability and personalisation, enabling devices to better interpret and respond to users' unique motor profiles and activity goals. The limited incorporation of machine learning approaches in AT design suggests that rehabilitation professionals should actively contribute to a wider demand for its application.
- Increasing participation of individuals with SMI in the evaluation of AT systems is essential for developing inclusive solutions that address diverse needs and enhance real-world digital engagement.

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/17483107.2026.2693221.

Introduction

Recent technological advances have enabled new, more efficient ways for individuals with motor impairments to interact with computer-based applications. Severe motor impairments often limit or prevent the use of standard human-computer interfaces, creating a need for devices specifically designed to accommodate varying motor abilities. According to the World Health Organisation report [1], ~190 million people—3.8% of the global population—experience "severe disability," which can limit their ability to perform daily activities, including computer-based tasks. "Disability" is an umbrella term encompassing different body function impairments, such as visual, auditory, cognitive, or motor impairments, as well as limitations in activities or restrictions in participation. Disability thus includes impairment, but is not limited to it, being the interaction between health condition and contextual (personal and environmental) factors [2].

"The World Health Organisation defines Assistive Technology (AT) as any product, instrument, equipment, or technology specifically designed or adapted to enhance the functioning of individuals with disabilities [2]. Several well-established frameworks guide the development, adaptation, application, and evaluation of AT, including Matching Person to Technology (MPT) [3], Comprehensive Assistive Technology (CAT) [4], and the Human Activity Assistive Technology (HAAT) model [5]. These frameworks' principles are grounded in user-centred design, recognising that functioning and needs can vary significantly from person to person. Therefore, AT systems should meet the specific needs of people with disabilities.

The HAAT model views assistive technology as an enabler that supports a person in performing activities within specific contexts [5]. This model highlights four key components: human, activity, assistive technology, and context. An effective AT system should align with the user's skills and abilities (e.g., head movement), the technology itself (e.g., a video-based head tracker), the activity being performed (e.g., moving a mouse cursor), and the environment in which it occurs (e.g., working in low-light conditions). The HAAT framework is widely used in AT research, and it emphasises activity as a core element of AT development.

A related concept, Body-Machine Interfaces (BoMIs), involves assistive devices that leverage users' residual movements to operate external devices. While the term BoMIs is somewhat broad and therefore debateable for research focusing on specific populations, it is used in the AT literature [6–10] and is useful for this review's focus. BoMIs are a subset of AT designed to convert users' body signals—such as movement, force, or neurophysiological signals—into control inputs for external devices, allowing users to extend their motor capabilities through their residual voluntary control.

BoMIs differ from Brain-Computer Interfaces (BCIs) in important ways. Unlike BCIs, which try to generate action triggers by identifying neural patterns that emerge from active or passive stimulus, BoMIs use residual voluntary movements, tapping into the fine motor control users retain [7]. This reliance on body motion is more intuitive, as controlling one's body is typically more natural than modulating brain activity [6,10]. Further, this point notes that the rate of information transmission *via* body movement can be 10–100 times faster than with EEG-based BCIs. For instance, in an experiment with able-bodied participants [11], moving a screen cursor with a joystick yielded information transmission rates of 3.96 bits/second, compared to 0.456 bits/second with a BCI. BoMI studies support the idea that using residual voluntary movements may help sustain muscle activity and potentially enhance motor skill rehabilitation.

Our target population includes individuals with severe motor impairments who retain some residual voluntary movement but excludes those with conditions like Locked-in Syndrome, where no voluntary control remains. Neuromuscular disorders such as Cerebral Palsy, Multiple Sclerosis, Muscular Dystrophy, or Spinal Cord Injuries can have a range of impacts, from mild to severe symptoms, affecting one or both sides of the body and possibly both arms and legs [12]. Symptoms may include muscle weakness, reduced muscle endurance, involuntary muscle contractions (e.g., stiffness, cramping), sensory loss, autonomic dysfunction, and impaired voluntary movement, which can affect speech [13].

Despite a growing body of work on AT for motor impairment, no structured synthesis exists that specifically maps how residual voluntary movements are captured, processed, and translated into the control of concrete digital tasks for SMI users. Existing reviews have addressed AT acceptance [14], methodological standards in motor impairment accessibility research [15], or broad AT access and policy [16], but none have systematically characterised the design landscape that includes control site and sensor selection through signal processing, mapping architecture, and quantitative evaluation of devices directed at functional digital task performance in this population.

Our primary aim is to identify and assess existing AT solutions that address the specific needs of individuals with SMI. This includes examining the required motor abilities, sensing technologies, target activities, mapping structures, and quantitative assessments of these devices. This review extends the scope of previously published papers by focusing on assistive technologies for human-computer interaction in individuals with SMI, specifically emphasising the use of residual movements, their mapping to intended digital tasks, and the evaluation methods employed by researchers. Our main research question was: Which devices support voluntary movement for SMI users to control computer applications, and how have researchers developed and assessed them?

Background

Assistive technology devices for computer access can be evaluated through a set of specific indicators that describe their design, functionality, and usability. One key indicator is the activity addressed, which refers to the device's primary goal, such as enabling text input, cursor control, or communication. Another important topic is the control site, the body location of the user, or a combination of locations, that is used for obtaining their volitional input into the system. Commonly used anatomic sites are hands, head, elbow/arms, eyes, mouth, chin, forehead, foot, and knee/leg [17]. In a test that assesses viable anatomic sites for input in a Human-Computer Interface (HCI) [18], there is an order of preferred sites, with the hands being the control site of choice and thus the first to be assessed. If the hands are not functional for control, the assessment continues to the site believed to perform better. HAAT also provides a similar sequential concept in a clinically based framework for optimal control site determination [5]. According to Sarsenbayeva et al. [15] many studies insufficiently justify control site selection and lack adaptive models capable of addressing diverse motor profiles. The choice of the control site guides the selection of proper input sensors and signal analysis for AT selection or development. There are many sensors that can convert body movement into a digital signal, and many ways to classify them. Some examples of sensors include switches, potentiometers, accelerometers, gyroscopes, inertial measurement units (IMU), electromyography (EMG), electrooculography (EOG), RGB cameras, depth cameras, infrared cameras, microphones, gesture recognition systems, electrodermal activity, force sensing resistors, electromagnetic tracking systems, sensing fabrics [19]. A system can be unimodal or multimodal, depending on whether the interaction is based on a single channel or integrates multiple input modes for coordinated interaction. A unimodal system uses a single input modality, typically speech or keyboard input, for interaction [20]. Multimodal systems process two or more combined user input modes—speech, pen, touch, manual gestures, gaze, head and body movements, and so forth—in a coordinated manner with multimedia system output [21]. Recently, wearable multimodal configurations combining IMU and surface EMG emerged as a growing area of interest for capturing residual upper limb movement [22,23].

In HCI research, the concept of an input device provides useful ways to describe the Human-Technology Interface (HTI) of assistive systems. In a seminal work, Buxton [24] introduces a taxonomy of input devices, categorising them by degrees of freedom and the properties measured (position, motion, or pressure). Degrees of freedom are a useful concept that relates to the number of independent variables the HTI sends to the processor. The data collected by the sensors must then be processed to represent meaningful information about the user's motion. This field of research, named signal processing, is a "fundamental component of almost any sensor-enabled system, with a wide range of applications across different scientific disciplines. Time series data, images, and video sequences comprise representative forms of signals that can be enhanced and analysed for information extraction and quantification" [25]. Recently, these processes have increasingly utilised artificial intelligence and machine learning, shifting from procedural to data-driven signal processing. Some examples of signal processing for body motion are gesture recognition, skeletal tracking, eye tracking, speech recognition, face tracking, and facial expression analysis [26].

Mapping is a technical term borrowed from mathematics that refers to the relationship between the elements of two sets. It was made popular in the field of HCI by Norman [27], who defined it as the relationship between controls and their effects on the world. In the HAAT model, it is closely related to the processor, translating the forces and information received from the human into signals that control the parameters of the task to be performed. A subset of the AT field of study in which this concept has been more developed is the construction of Digital Music Instruments (DMIs). DMIs are composed of an input device that takes the control information from the performer, a sound generator prepared for real-time control signals, and a mapping layer connecting them [28]. The complex interconnection of control and musical parameters has led to extensive research on this topic in the DMI field [29], yielding concepts we can use to characterise this component of the assistive device in the selected articles. Depending on the arrangement of connections between the input signals and the digital task parameters, we can define the mapping topology [30]. A simple case in which a single input signal is connected to a single destination parameter is considered a one-to-one mapping. If multiple source parameters are combined to control one destination parameter, it is defined as many-to-one; one source signal controlling several destination parameters is one-to-many; and when multiple source and destination parameters are complexly connected, we name the topology many-to-many. A mapping system that connects the input and output directly is considered to have one mapping layer. It is sometimes useful to create additional layers of mapping that allow the use of abstract or derived variables related to the input signals or output parameters, which can provide more meaningful concepts for the interaction design [30]

An important distinction is between explicit and implicit mappings [31]. In explicit mappings, the relationship between input and output is clearly defined by the system designer, who provides all the procedures for their connection, thereby enabling a deep understanding of the effectiveness of mapping choices. In implicit mappings, the connections are defined by a Machine Learning (ML) algorithm, considered a "black box approach" in which the designer can benefit from the self-organising capabilities of the ML system. Supervised ML is guided by human preferences through training of the system (support vector machine, artificial neural network), and unsupervised ML uses the structure found in the data alone - hidden Markov model, K-means [26].

In quantitative analysis, Randomised Controlled Trials (RCTs) are the gold standard. However, due to diverse, small user populations and ethical issues surrounding placebo controls, they pose challenges in AT [32]. Alternative methods, such as single-subject designs and repeated-measures or crossover studies, are often more practical [33]. Recent literature emphasises the significance of usability—encompassing testing methods, interviews, and task analysis—as a primary approach in assistive technology research. For instance, in a review on AT assessment [34], eleven of the seventeen examined papers employed task-based usability tests with prototypes, often using participants without disabilities, thus limiting real-world applicability [15] review corroborates these results with reports of small samples and high use of able-bodied participants in laboratory settings, raising concerns regarding the ecological validity and generalisability of findings to real-world contexts. Key usability measures include success score, error rate, task time, time-based efficiency, and combined metrics that integrate performance and time data. These metrics align with the ISO 9241-11 [35] framework, which defines usability in terms of effectiveness, efficiency, and satisfaction. Instruments like the System Usability Scale (SUS) and NASA-TLX further capture subjective aspects of user experience [36,37].

Materials and methods

In accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines [38], a comprehensive search strategy was deployed utilising database-specific field tags and Boolean group nesting to ensure total transparency and study reproducibility. The search string's performance and structural logic were validated *via* an iterative internal peer review by the three co-authors to satisfy the reporting standards of PRISMA-ScR.

Information sources

We included written/published works between 2012 and June 2024 and conducted the search between July and December 2024. We selected 2012 as the start date because several emergent technologies relevant to assistive technology became available to the public during this time, such as Tobii eye tracking, the announcement of Leap Motion and Google Glass, the mainstream availability of touchscreens and 3D printing, and the release of the Kinect SDK. We used Scopus and Web of Science Core Collection as databases and considered conference proceedings and journal papers written in English.

Inclusion and exclusion criteria

The inclusion criteria were:

1. An assistive device for the performance of a digital task must be presented
2. The presented device must be directed to SMI users
3. A quantitative device assessment must be included
4. The publication must be in English
5. Publication date must be between January 2012 and June 2024

The exclusion criteria were:

1. Not related to SMI
2. No computer-based digital task or only a rehabilitation goal
3. No quantitative assessment of device performance
4. Not focused on device implementation
5. Not English
6. Less than 4 pages

For inclusion in the review, the devices must have clear activity goals. Research on a device for digitising residual voluntary movement in subjects without its application to functional tasks is lacking in most of the intended analysis topics for this review. Despite the authors referring to an intended activity goal for the device, if control parameters specific to the tasks associated with that activity were not included in the system or its evaluation, we did not consider the article for analysis. Similarly, rehabilitation devices that serve no purpose beyond their primary recovery function are redundant in mapping a user's movements to an activity goal. These devices primarily work by either constraining or stimulating existing motion patterns. While they may offer insights into systems that collect users' motion data, they do not explore functional connections between movement and activity goals. As a result, they fail to address a key component of the HAAT model. Studies using BCI as the user's acquisition device were not included, as such papers do not focus on physical movement. Systematic or scoping reviews were also excluded because they do not delve into the details of the devices studied.

Search strategy

We conducted initial controlled vocabulary searches to achieve a balanced relationship between keywords and relevant results. The final syntax to search the title, abstract and keywords of both databases was:

(("computer inter*" OR "body-machine inter*" OR "assistive technolo*" OR "HCI" OR "Interaction design*" OR "digital music* instrument*") AND ("motor impairment*" OR "motor disabilit*" OR "cerebral palsy" OR "physical disabilit*") AND NOT ("BCI" OR "EEG" OR "brain-computer" OR "review")) AND PUBYEAR > 2012.

After removing duplicates, we examined titles and abstracts to identify and exclude documents related to aspects of assistive technology beyond the scope of this review, using the inclusion criteria. In cases of ambiguity, we retained papers for the next stage of full-text review. From this metadata screening, we derived the list to be assessed in the complete reading of the studies. This assessment for inclusion in the analysis stage was performed using a set of exclusion criteria. Studies were included only when none of the exclusion criteria applied.

Appraisal, data extraction, and data analysis

To ensure consistency in analysing the articles and their respective devices, we established coding rules. We constructed a classification scheme based on the selected literature cited above. For the papers included in the dataset, we systematically analysed the devices using a set of predefined categories: publication information, target motor disability, activity addressed (device goal), control site, sensors, signal processing, mapping of the input data to control parameters, topology, number of layers and use of

ML, adaptation to specific motor qualities of the user, feedback of the system, population, and dependent variables of quantitative evaluation.

During data analysis, when a device offered several options, we treated them as independent variables. For example, if a device used both an EMG sensor and a video camera, we counted these as separate entries in the sensor category rather than combining them into a single value. As a result, the total number of sensors used exceeds the number of included devices. We believe this approach increases the significance and readability of the results by reducing the number of options displayed and providing a more accurate global representation of the design options of the devices.

In addition to extracting and analysing individual indicators, we performed cross-analysis of several topics using relationship and correspondence techniques. To optimise this process, we unified various profiles into larger categories based on functional similarities. For instance, we grouped the Force-Sensitive Resistor (FSR) with switches in the sensor topic for cross-analysis with other issues, since the FSR was primarily used as threshold-based signal processing, making it functionally like a switch in the context of this review.

Results

We identified 2056 articles from the database search, of which 367 passed the inclusion criteria after screening their abstracts. We retrieved the full text of 342 of these articles and assessed them for eligibility, resulting in 49 articles included in the review (see Figure 1).

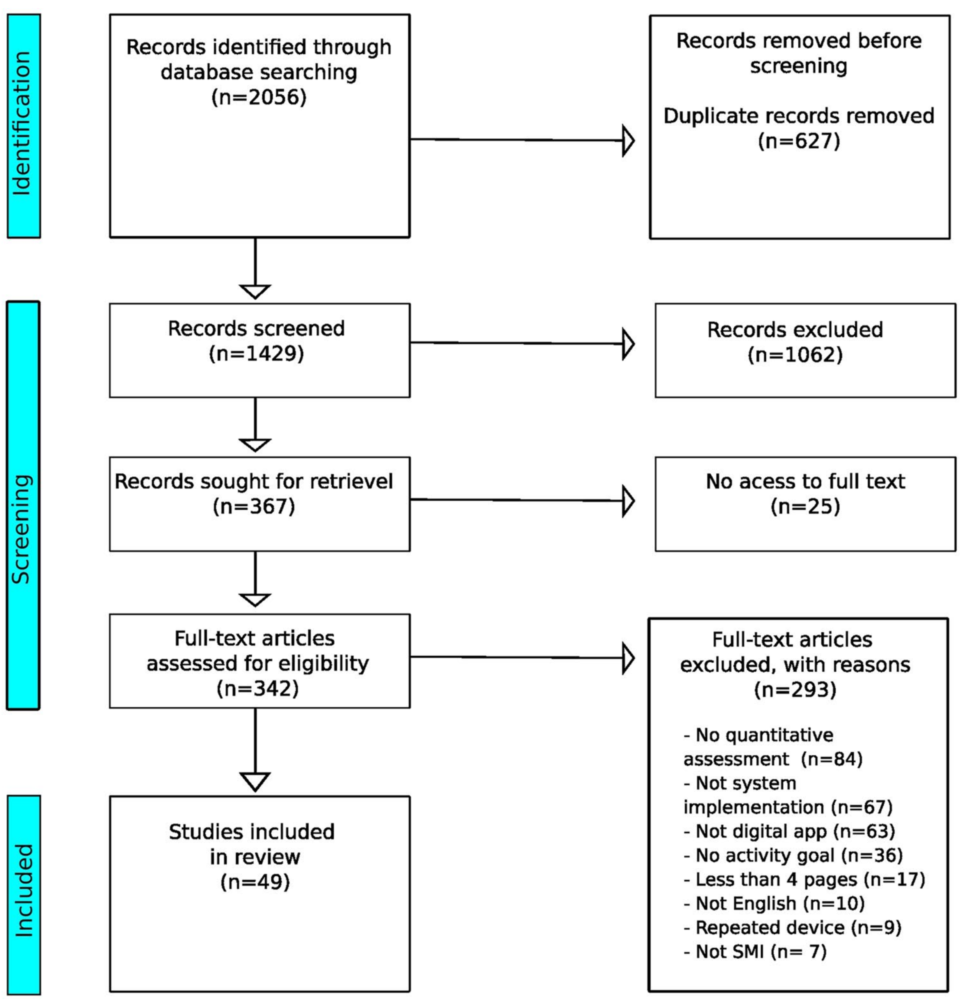

Figure 1. PRISMA-ScR flow diagram (Page 8).

The reviewed studies were published across a wide variety of venues, with most journals or conferences represented only once. However, a few outlets are notably more frequent: IEEE Transactions on Neural Systems and Rehabilitation Engineering appear four times. Both the International Journal of Human–Computer Studies and Universal Access in the Information Society appear three times each. Additionally, seven venues are represented twice. Overall, publication types are relatively balanced, though journal articles (28) slightly outnumber conference papers (21).

In relation to the target motor disability profile, almost three-quarters of the articles are not specific about the type, focusing on a more generic definition of SMI. Spinal cord injuries, cerebral palsy, and motor neuron disease (mainly amyotrophic lateral sclerosis) represent the main targets in articles that possess a specific type of motor impairment. Most devices use a single input modality, with only 20% offering a multimodal solution. Two-thirds of the devices include some form of adaptation to the user's specific motor qualities. These are obviously very characteristic of the implemented system, but we can notice the tendencies of calibration of the sensor values to the range of motion of the user, found in the calibration of transfer functions from usable IMU or EMG values to the activity parameters, and Gaze-tracking calibration, with the latter being the most prominent.

Control site

The most used control site is, by a large margin, the head – Table 1. Devices that use the eyes represent 28% of the used control sites, and the sum of head spatial orientation, facial expression, and nose orientation comprises 32%, giving a total of 60%. Of the analysed systems, 12% were designed to be adaptable across different body locations. Although less prominent, the total use of shoulders, elbows, legs, and feet comprises another 12% of the chosen locations for interaction points. Hands are used in only 8% of devices.

Table 1. Number of articles by 'control sites'.

Control sites	Count
Eyes	18
Mouth	8
Adaptable	8
Nose	5
Hand	5
Head	5
Shoulder	4
Voice	3
Foot	2
Face	2
Head	1
Tongue	1
Elbows	1
Leg	1
Fingers	1
Total	65

Activity

The main goals registered were, by a large margin, the wide-ranging tasks of controlling the pointer and text input. Together, these navigation and writing tasks account for more than 60% of the devices, with an additional 24% attributed to devices with related tasks. More specific undertakings, like playing DMI's or video games, only comprise 10% of the total. The main feedback in most activities is visual, except for playing DMI instruments, which is an obvious result of this specific activity. Regarding auxiliary feedback, three-quarters of the articles do not mention any solution, 18% mention audio cues to complement the interaction, and 6% mention haptic responses.

Sensors

Table 2 shows the most used sensors, with the first five accounting for more than 50% of the 17 reported. Non-intrusive visual-based systems (Video cameras and eye trackers) were the main choice, closely

Table 2. Number of articles by 'sensors'.

Sensors	Count
Video-camera	9
Eye tracker	7
EMG	7
IMU	7
EOG	6
Microphone	4
FSR	3
Depth-cameras	3
Touch screen	2
Accelerometers	2
Electromagnetic tracking	2
Microswitch	2
Gyroscope	1
Scroll-wheel	1
IR reflectance sensor	1
Sip/puff	1
Switches	1
Total	59

followed by more intrusive and time-consuming sensor setups such as IMU, EOG, and EMG. The analysis revealed no statistical significance in the distribution of sensor use per year during the timeframe of this review.

Signal processing

The most used signal processing technique in research was thresholding, used in more than one-third of the solutions, followed by motion tracking (20%) and facial and gaze tracking (14%) each.

Mapping

About 20% of the articles use ML for mapping input data to control parameters, with supervised learning accounting for more than two-thirds of these. The remaining devices use explicit mappings. Of these explicit mappings, the most used topology is the most direct, with one-to-one correspondence accounting for 63% of the revised systems. Systems with one layer of mapping equal 72%, leaving 28% of cases with an added layer for further conceptualisation of input movement or output parameters.

The analysis of the correspondence between the number of inputs and controlled parameters shows an association, meaning devices with more inputs tend to control more parameters, but it is not a strict linear relationship. Most devices use 1 to 3 independent inputs from the user's control sites, accounting for 65% of the total. There are still 19% of cases that utilise four or five inputs, and from there up, they become progressively less common. The percentage of controlled parameters is similar, except for activities with three controllable parameters, which represent 37% of the devices, while devices with three inputs represent 19% of the total solutions.

The average number of inputs is 3.71 (standard deviation of 3.57), and the average number of Controlled Parameters is 2.98 (standard deviation of 2.46). If we compare the number of inputs to the number of parameters per case, we find that 48% of cases have equal numbers of inputs and outputs, 28% have more inputs than outputs, and 24% have more outputs than inputs.

The analysis of input-output relationships across different layer categories reveals that single-layer devices tend to favour a 1:1 input-output correspondence. One-to-One and One-to-Many mappings consistently maintain a single-layer structure, reinforcing their direct input-output correspondence. One-to-One mappings always exhibit an equal number of inputs and controlled parameters, while One-to-Many mappings exclusively have more outputs than inputs. Many-to-One and Many-to-Many mappings, on the other hand, frequently involve more inputs than outputs and are more likely to utilise an additional layer in a more complex system.

Quantitative evaluation

Of the total experimental population, 52% were able-bodied subjects, and 6% did not mention the motor ability of the sample subjects. In the remaining 42% of experiments that used subjects with motor impairment, 14% did not specify beyond SMI; among the rest, we identified several types, namely Cerebral Palsy, Amyotrophic Lateral Sclerosis (ALS), Spinal Cord Injuries, and Muscular Dystrophy. The average sample size for able-bodied participants is 9.6, and for experiments with participants with a form of SMI, it is 6.6. The main dependent variable used in the quantitative evaluation of the systems' achievement of the digital task is, by far, task time with 47%, followed by error rate with 29%. Although less prominent, effectiveness and precision remain relevant, accounting for 11% and 8% of the metrics used, respectively.

Activity - sensor

To facilitate interpretation, we grouped related tasks under one topic—typing on a virtual keyboard—which will also include block scanning for typing on a virtual keyboard, Morse code typing, and phoneme selection. The topics of controlling the computer mouse, block scanning navigation, and touchscreen navigation are included in the navigation topic. There is a clear tendency in the navigation tasks to use video-camera and IMU sensors. In communicative tasks, the main choices are eye-trackers, EOG, and EMG. In the less-researched task of playing computer games, the used sensors were a depth camera and a video camera; in the task of playing a digital music instrument, both devices used eye-trackers.

Activity - control site

Eyes and head are used across multiple activities, making them the most adaptable inputs for diverse tasks, as expected given their dominant role in that category. The typing activity confirms this tendency, with the sum of eyes and head control representing 63% of the used sites. The control of the mouse task is, although mainly achieved through head-related data, also used as input across multiple control sites, including the eyes, hands, upper arm, and tongue. Lower limbs are only used in typing tasks.

Control site – sensor

The analysis of the correspondence graph (Figure 2) between control sites and the sensors used to digitise their movements reveals an obvious trend: dominance of eye-tracking for the eye control site, and microphones for voice. In a less self-evident manner, we can note that the spatial orientation of the nose and head, mainly used for controlling the computer mouse, uses different digitisation approaches: the nose is only tracked by video cameras, while head orientation is tracked almost exclusively by IMUs. The hands mainly use switches and touchscreens, and the lower limbs IMU's. The systems with adaptable control sites use EMGs, cameras, and switches.

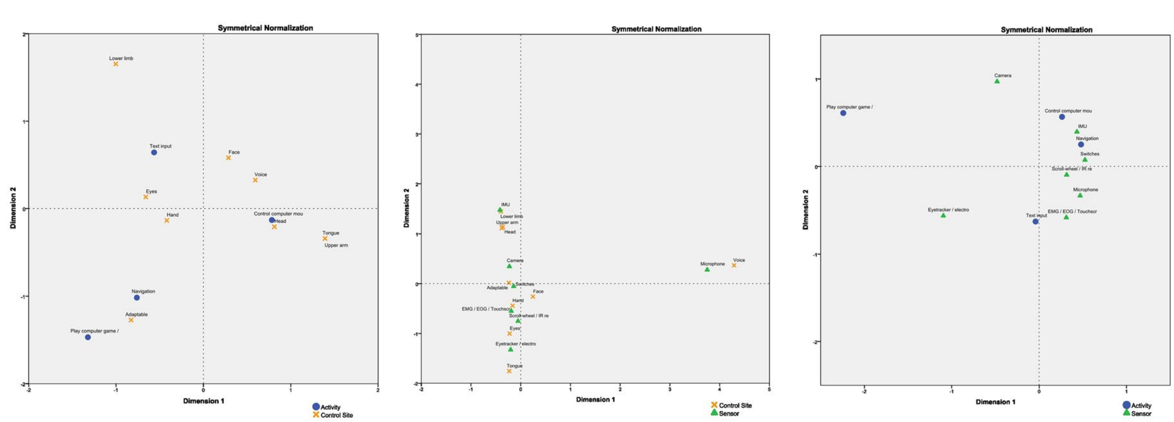

Figure 2. Simple correspondence analysis between activity vs control site (left figure), control site vs sensors (center figure) and activity vs sensors (right figure) (Page 11).

Areas of attempted SMI optimization

This is the result of a subjective analysis of the systems described in the articles to evaluate the development focus aimed at optimising the performance of the activity for SMI users. It is considered, in a very general way, the most frequently described and innovative components of the systems in the articles and the object of the quantitative evaluation. Three categories were assumed: digitisation, processor, and feedback. The first corresponds to the input phase, with a focus on sensor technologies and signal processing for extracting features from voluntary movements. The processor is centred on the mapping options for the connection between input and output parameters. Finally, feedback encompasses the concern in the output, whether in the GUI configuration or in other options such as auxiliary audio or haptic responses. We considered that 60% of the articles focus on the process of capturing voluntary movements, and the remaining is split closely between the processor and feedback, with nearly 20% each. Also noted that most cases involving feedback optimisation involve typing activity, with different keyboard configurations to facilitate access.

Discussion

The diversity of publication venues highlights the interdisciplinary nature of research on assistive technology (AT) for individuals with severe motor impairments (SMI). In a context where most venues appeared only once, a few journals, such as "IEEE Transactions on Neural Systems and Rehabilitation Engineering", "The International Journal of Human-Computer Studies", and "Universal Access in the Information Society", emerged as leading sources.

The prevalence of the reviewed studies addressed SMI in a general sense rather than focusing on specific underlying conditions or movement profiles, suggesting a tendency towards designing broadly applicable solutions rather than tailoring systems to specific impairments. This generic SMI target group mirrors a broader pattern identified by Sarsenbayeva et al. [15], who found that studies consistently fail to account for the high inter-individual variability of motor profiles, defaulting instead to broad impairment categories that obscure clinically meaningful differences between users. Most of the devices included some form of adaptation to the user's specific motor abilities, aligning with best practices in AT [5], which could be reasoned as a compensation for this generalised approach in such a user-specific context. In closer analysis, we observe that these adaptations mainly materialise in the calibration of the sensors data or the signal processing techniques for specific thresholds of movement or ranges of motion of the chosen control site. These scaling of thresholds for activation and usable range of motion provide useful tailoring for specific abilities of the user, but are always related to fine-tuning of the chosen control sites and sensor modality of the system. Therefore, they are adaptations that do not significantly expand the SMI typology of possible users of the device beyond those that exhibit functional control in that specific conjunction of body site/sensor pairing.

This generic SMI target group, associated with the low percentage of adaptable control sites or multimodal input and the narrow scope of motor impairment typologies most implemented adaptations allow, suggests a trend for researching generic/serve-all solutions that don't account for the high variability of individual motor profiles, a view found in accordance with some recent AT research [39–41]. We can argue that it is very difficult, albeit impossible, to create universal devices in this SMI context and that the creation of devices for very specific motor profiles can be a practical solution. It would be recommendable then to define in an explicit and precise manner these profiles in each device to facilitate AT selection for specific individuals wanting to perform an activity or instead create devices that aim to be "adaptable and modifiable, thus leading to the principle of extreme adaptability" [39]. The ability-based design framework [42] offers a concrete design alternative here, where rather than calibrating a fixed system to a user's residual range, ability-based systems adapt their interface dynamically to context and performance. This direction shifts the burden of accommodation onto the system rather than the user, but it was largely absent from the reviewed literature.

A significant majority of the devices utilised a single input modality, suggesting a preference for simplifying input mechanisms that can lead to "extreme fatigue, over-use injuries, inaccurate control, and inefficiency" [43] versus the exploration of sensor fusion in multimodal configurations, despite the potentially desired increase in bandwidth of volitional motor input of the former. In contrast to conventional HCI, where the hands are the primary control site, few AT systems rely on manual input. Instead, head-based control was dominant, with participants with limited hand function achieving significantly higher accuracy in target acquisition tasks using head tracking than with hand-operated devices. These results are in concordance with Simpson and Koester [44], which states that "users with conditions like muscular dystrophy or cerebral palsy frequently exhibit better control over gross motor movements (head, trunk) than fine finger motions, making head tracking a more viable input method". This preference is further supported by clinical AT assessment frameworks: both Fraser et al. [18] and the HAAT model [5] establish a sequential hierarchy of control site evaluation, in which the head is assessed immediately after the hands prove non-functional—making its dominance in this review not an arbitrary design choice but a direct reflection of established clinical practice. With this common inoperability of the hands in severe motor impairment, it can be argued that the choice of the head as the primary control site is in line with the mapping of the motor cortex [45], where the head occupies the second largest area of motor control, after the hand and fingers. The most used sensors were non-intrusive vision-based systems (video cameras and eye trackers), followed by IMUs, EOG, and EMG. The lack of a significant temporal trend in sensor usage suggests that there has been no major shift in hardware preferences over the years. In terms of signal processing, threshold-based techniques were, by far, the most frequently employed. It is predictable that thresholding will be used in many systems, since it is a basic logic building block for binary selection, but the fact that almost half of the included devices used solely that technique is an indicator that a relatively simple global approach to the system design is still being widely used.

The primary functions of AT systems overwhelmingly revolved around pointer control and text input. The universality of these tasks in digital environments likely drives this trend, with the interaction techniques maintaining the 2D paradigm based on “widgets such as menus and icons” [46]. In the mainstream, able-bodied desktop HCI, text input is primarily done through a keyboard or screen-based virtual keyboard, which has high input data bandwidth due to using fine motor control of the hands as a control site [47]. In the reviewed systems, this specialised hardware is translated into virtual keyboards with character selection being based on pointer control or some form of scanning. Although many researched devices try to overcome the barriers of this “need for controlled hand movements” [48] utilising alternative methods of motor input and digitalisation, they still maintain the universal interaction model known as Windows, Icons, Menus and Pointers (WIMP) [49]. WIMP is a universal interaction paradigm used for the control of most applications in commercial HCI, where only the GUI varies relative to the specific task at hand, while the 2D pointing to icons and menu concept is maintained. It is a useful model, standardising an intuitive and consistent interface across diverse applications, allowing users to transfer skills from one program to another, but this universality has a trade-off at the expense of more specialised, efficient, and natural interfaces, a view defended in Andries van Dam’s concept of post-WIMP user interfaces. A post-WIMP approach is less reliant on a universal paradigm but instead creates very specific interaction models related to the properties of the task being executed by choosing specific input/output modalities and optimised mappings of input to application parameters. In this review, more specialised applications, such as DMI interaction and video game control, were considerably less represented. The design of devices directed at more specific tasks could help maximise SMI users’ abilities and overcome barriers to efficient control.

The Mapping component showed low usage of ML, a relatively recent technology, but with many possible useful applications like multimodal integration of input signals [50] or personalisation and adaptation to individual motor profiles [51]. Most devices using explicit mapping had simple mapping processes, with predominant use of one-to-one correspondence between inputs and outputs. More complex topologies—many-to-one, one-to-many, and many-to-many—are considered essential for instruments that seek to maximise the relationship between performer gesture and output [30], precisely the challenge AT devices face in translating limited residual movement into rich digital control.

Devices with multiple processing layers exhibited greater flexibility in input-output transformations, suggesting that more sophisticated interaction models require additional computational processing. The association between the number of input channels and controlled parameters supports the expectation that systems with more complex input mechanisms tend to offer finer control, though the relationship is not strictly linear.

Visual feedback was the predominant mode across most systems, which aligns with the nature of tasks like typing and navigation and the already mentioned WIMP paradigm. Few studies addressed auxiliary feedback mechanisms, with some examples of audio cues and haptic responses incorporations. This limited attention to multimodal feedback highlights an area for potential improvement in AT design, as alternative feedback methods could enhance usability for individuals with severe motor impairments [52]. Multimodal feedback can create more robust and efficient control by combining modalities and their different strengths [53].

The quantitative evaluation of AT systems revealed a significant reliance on able-bodied participants. Among studies involving individuals with motor impairments, sample sizes were generally small (average of 6.6), potentially limiting the generalisability of findings. Task completion time and error rate were the most-used performance metrics, reinforcing the field's focus on efficiency and accuracy in digital task execution. When evaluated against the ISO 9241-11 [54] usability framework, which defines usability across effectiveness, efficiency, and satisfaction, the metrics employed in the reviewed literature address efficiency and partial effectiveness, while satisfaction falls outside the quantitative scope of this review. Within the dimensions that are measurable quantitatively, however, the dominance of task time as the primary dependent variable warrants scrutiny in the SMI context. Task time is well-established in mainstream HCI, where it underpins formal models such as Fitts' Law for pointing performance. However, its straightforward application to SMI populations is complicated by the fact that movement speed is often constrained by motor impairment itself rather than by interface design, making cross-study comparisons of raw task time difficult to interpret without normalisation against individual baseline performance. The reviewed literature shows little evidence of such normalisation, suggesting that efficiency as currently measured may reflect user motor capacity as much as device quality—a conflation that limits the conclusions that can be drawn from comparative evaluation across studies.

Limitations

Our scoping review carries certain methodological limitations regarding reporting transparency and search verification. Although the literature search strategy was rigorously structured and fully documented to meet the core reporting standards of the PRISMA-ScR checklist, its protocol was not registered, and it did not undergo evaluation by an independent, external information specialist. While our internal co-author consensus process optimised subject-matter alignment and verified database-specific syntax translation, the lack of an external librarian audit introduces a vulnerability to shared perspective bias, potentially omitting alternative terminology or obscure indexing frameworks that an independent reviewer might have identified.

The use of the exclusion criteria for publications without quantitative assessments was the strongest rejection factor in the screening process. We consider this option to have removed some accuracy in the representation of current trends within the field, especially in terms of the activity goals' results. One of the reasons for the very high incidence of typing and navigation activities could potentially be due to the well-established experimental methodologies for their quantitative analysis, favouring the inclusion of publications with these activity goals. Other tasks, like assistive DMI design, with more complex and less established quantitative methodologies, will likely have a higher focus on qualitative assessment, if any are present. Nevertheless, we believe this option allowed to select studies that dwelled into the developed model beyond their description, providing a structured overview of how residual movements are quantified, transformed into actionable digital commands and identifying assessment techniques used by the researchers in AT assessment.

Conclusion

The landscape of AT research was directed at a generic target group of SMI users, emphasising head-based control and pointing interactions in two-dimensional GUI interfaces aligned with the WIMP universal approach, for standard digital interaction tasks like typing and navigation. Regarding how researchers have developed these devices, the reviewed literature reveals some visible trends. Interaction points were repositioned towards body sites where voluntary motor control is more commonly preserved, with sensor selection following the same principle. The predominant development effort concentrated on the reliable capture and digitisation of the movements present in these control sites, complemented by calibration to individual motor ranges. The translation of this input into application control was achieved through predominantly direct and simple mapping solutions. Since most devices do not offer adaptable control-site location or only provide narrow adjustments to specific motor profiles, it would facilitate AT selection for particular individuals if the articles narrowed the end-users more explicitly with precise and explicit target motor profiles. While the field has made significant strides in sensor technology and signal processing, there remains room for improvement in multimodal input/feedback solutions and in using ML to increase adaptability to specific motor profiles. We suggest that a post-WIMP approach could increase task efficiency by exploring novel use cases beyond conventional computing tasks, with specific interaction models related to the properties of the task being executed. Future research should aim to address these gaps and expand participation among individuals with SMI, increasing their involvement in the development and evaluation of AT devices.

Author contributions

CRediT: **Bruno Afonso**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing; **André Perrotta**: Conceptualization, Methodology, Writing – review & editing; **Joaquim Alvarelhão**: Conceptualization, Formal analysis, Methodology, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

National funds from FCT partially financed this work - Fundação para a Ciência e a Tecnologia, I.P., in the framework of the Doctoral research grant 2021.04786.BD. André Perrotta is funded by national funds through FCT – Foundation for Science and Technology, I.P., within the scope of the research unit UID/00326 - Centre for Informatics and Systems of the University of Coimbra, https://doi.org/10.54499/UID/00326/2025.

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