# Characterizing “Motor Ability” for Ability-Based Design

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## ABSTRACT

Ability-based design (Wobbrock et al. 2011, 2018) offers conceptual guidance for its use in designing accessible systems, but the construct of “ability” itself—a crucial notion for ability-based design—is surprisingly elusive and absent from extant accounts. Different disciplines offer disparate notions regarding definitions and measures of “ability,” but ability-based design has yet to avail itself of these notions in its operationalization. To address this gap, this work reviews literature that quantifies motor abilities, provides guidance to distill metrics for human-computer interaction, and conceptualizes how motor ability should be quantified for ability-based design. We offer a three-dimensional framework composed of the user, context, and task, and we locate various metrics for ability to be used when implementing ability-based designs. We support this new conceptualization with example personas that occupy this three-dimensional space. This work can inform those using ability-based design to create systems that are responsive to users’ abilities.

## CCS CONCEPTS

• **Human-centered computing → Accessibility theory, concepts and paradigms**; **User models**.

## KEYWORDS

accessibility, ability, human motor control, ability-based design

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## 1 INTRODUCTION

“Ability” is a core, but often *implied*, concept in human-computer interaction (HCI) and accessibility; for example, speech-language pathologists work with patients to assign augmentative and alternative communication (AAC) technologies based on patients’ abilities [19], usability professionals study how fast and effectively users are able to navigate through websites [11], and researchers measure text entry efficiency when evaluating new input devices [135]. These engagements with “ability” in HCI and accessibility are often unidirectional in the sense that information is obtained about the design of systems based on their usage, but systems come to learn nothing of their users’ abilities and have no capacity for representing those abilities even if they did [124, 125]. By contrast, some authors have envisioned a more bidirectional user-system relationship, where a user acts on a system through their abilities, and the system responds to the user accordingly. For example, Gajos et al. [25–27] showed how desktop user interfaces could be automatically generated in response to a user’s observed abilities as demonstrated in a testbed. Evenson et al. [18] described systems designed to respond to users’ latent abilities as they arise in dynamic worlds. Wobbrock et al. [124, 125] articulated a vision of *ability-based design*, where systems model and respond to a user’s situated abilities. However, even Wobbrock et al.’s articulation of ability-based design stops short of conceptualizing what “ability” actually means.

Ability-based design [124, 125] is now over a dozen years old, and has highlighted the importance of developing computing systems that are responsive to users’ abilities. Numerous researchers and designers have engaged with the concept, including for young adults with intellectual disabilities [7, 8], psychomotor and cognitive user modeling for wheelchair users [40–42], smartphone interactions for older adults [90–92], children with motor disabilities [110], improving pointing techniques in graphical user interfaces [120], and for designing accessible outdoor activities [2]. It has even inspired Android applications capable of detecting certain abilities and recommending suitable assistive technologies [118]. But despite its uptake, ability-based design has never satisfactorily articulated “ability.” For a concept so central to this design perspective to have remained unexamined is concerning; we therefore aim to address that omission in this work.

Most manifestations of ability-based design take piecemeal and *ad hoc* approaches to considering or modeling ability, approaches that are narrowly in service of the creation of a specific product but that lack any deep engagement with ability itself (e.g., [25, 70, 71, 91]). These disparate manifestations reflect the limited understanding of how to utilize models of ability *beyond* HCI that clinicians and researchers in other fields have developed. As interactive technologies become increasingly informed by and deployed in other fields’ settings (e.g., medicine, therapy, social science, sports), understanding “ability” through these models as whole-body, socioeconomic, situational, and environmental phenomena becomes increasingly important. Thus, to further ability-based design, a deeper consideration of ability must be made, one that enables new approaches to conceptualizing, measuring, or modeling ability as


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translatable across devices, interfaces, contexts, and activities, allowing for "ability" to be usefully reified by interactive computing systems.

In this work, we move from implicit notions of ability to concrete notions of ability in order to solidify this construct for ability-based design. We focus on motor ability to demonstrate this move to concrete notions of ability—using metrics that characterize motor ability and relating these metrics, and "ability" more generally, to conceptual user models [74]. In so doing, we argue that for a system to robustly consider ability, it must: (1) consider metrics for ability within and beyond the field of HCI; (2) consider inputs that arise from a variety of data-capture methodologies and sources; and (3) consider how metrics complement and attenuate each other. This work highlights the multifacted nature of motor ability, and ability more broadly, through the synthesis of multiple definitions and metrics for these concepts across fields.

## 2 RELATED WORK

In this section, we review the research efforts that are similar to ours, namely that have attempted to clarify the notion of "ability" in some respect. As there have been relatively few such efforts and many of these efforts used constrained definitions of ability, this section focuses only on salient examples; however, the rest of this paper is devoted to reviewing, organizing, and synthesizing how other prior work, especially in disparate fields, has shed light on "ability."

Nolte et al. [74] described how considering the intertwining nature of users, tasks, and contexts is imperative when designing a system using ability-based design. They described a modification of conceptual user modeling that emphasizes the union of task, user, and context. While Nolte et al.'s framing builds upon ability-based design, it offers little information on how designers and researchers can define or measure "ability" itself for each of task, user, and context [73]. We build on Nolte et al.'s work by examining how task, user, and context can be solidified with a firmer notion of "ability" in hand.

Other work that touched upon a conception of "ability" was Vanderheiden's vision for a Global Public Inclusive Infrastructure (GPII). This project, formulated independently of ability-based design but consistent with its goals [124], proposed an infrastructure that could enable ability-based design [112–117]. Specifically, the GPII aimed to facilitate researchers, clinicians, developers, families and others the ability to customize information and communication technologies to their personal needs, aligning with ability-based design's goals of creating accessible technology by placing the burden of adaptation on the technology, not the user. The GPII's authors outlined a specific example implementation, the Library GPII System, which infuses the information and communication technology resources that libraries provide with the infrastructure enabled by the GPII, to create more inclusive libraries that facilitate access to information for everyone [113]. Recently, the team has created and tested an implementation of the GPII called *Morphic*, which eases access to a computer's accessibility features through a large button strip as well as a system that saves users preferences for persistence across devices [111]. However, Morphic relies upon users to specify their preferences for accessibility modifications, rather than automatically adjusting to observed or reported abilities.

Kondraske developed an early PC-based human performance measurement system [50, 51] that quantified a user's motor control, coordination, stability, and range of motion, among other things. While this system looked to comprehensively measure human performance, it's ability to translate its measurements on specific computer input tasks to a general notion of "ability" is limited.

Similarly, Koester et al. created a PC-based ability assessment system called *Compass* [47]. Compass had four components, including a client interface for ability assessment, a clinician interface for test configuration, a data visualization interface for viewing results, and a tele-rehabilitation interface for conducting remote assessments. Compass primarily covered keyboard, pointing device, and single-switch use. It was shown to be a valid and reliable means of assessing these computer input abilities [48, 49], but did not broaden beyond such abilities.

Building off this tradition of PC-based test beds, Gajos et al. devised the notion of an "ability-based user interface," which could be automatically generated by their system, *SUPPLE* [24–26]. Gajos et al.'s test bed involved mouse clicking, pointing, movement, dragging, and list selection. These behaviors were captured with regression models and used by a decision-theoretic interface generation algorithm that could minimize the "cost" of operating a user interface, which was shown to be more successful for people with motor disabilities [27]. Along with a user's motor abilities, SUPPLE could take into account a user's preferences as well [24, 25].

Persad et al. described how to measure human capabilities to support inclusive design evaluations [80]. They provided guidelines for designers, describing sensory, cognitive, and motor capabilities, and their respective lower-level categories. Specifically, for motor control, they distinguished upper-limb capabilities and gross body-movement capabilities. This work was extended through a topological data analysis of these categories through 39 measures of ability [79]. This work also clustered individuals by varying capability types, thereby creating granular personas, but it offered a rather limited view of "ability," not considering any environmental, contextual, situational, social, or other factors.

Reyes-Cruz et al. provided specific competencies that blind or low vision individuals develop to carry out various tasks [84]. Their work supports the claim that disability is largely structural, highlighting the unique routines and preferences individuals with disabilities must employ. They argue that these competencies should be considered "abilities" in any system that attempts to embrace ability-based design.

Similarly, Johnson et al. examined "capability" and how to measure it for the purpose of providing a database for inclusive design [44]. They compared measurement types, ultimately outlining the need for measurements that encompass activities, tasks, product interactions, and component functions, which are measurements that are not centered around specific activities.

These prior efforts somewhat conceptualize or operationalize "ability" in limited, implied ways, offering some guidance for how to incorporate measurements of ability in HCI. But none of them tackle "ability" head on. We follow Nolte et al.'s [74] integration of task, user, and context to develop a three-axis space in which measurements of ability can be placed.

# 3 TOWARDS CHARACTERIZING “ABILITY”

“Ability” is a large and somewhat intractable concept. Therefore, in our efforts to carefully consider ability, we focus on motor ability, demonstrating that even a narrow aspect of ability can be exceedingly rich and nuanced. We approach this task by surveying metrics that have different data sources (e.g., observational *vs.* self-reported) as well as different data types (e.g., qualitative *vs.* quantitative). By reviewing a large number of metrics that attempt to capture some aspect of motor ability, we show that expanding beyond metrics used in human-computer interaction (HCI) to characterize “ability” provides a rich view; indeed, these metrics can be utilized in HCI as well.

We sourced classification schemes for “ability” from medicine, rehabilitation engineering, physical and occupational therapy, biomechanics, sports science, ergonomics, and HCI. To extract a fair and representative picture of ability across these fields, we identified relevant literature through multiple mechanisms: overall query searching, forwards and backwards snowballing, and field-specific query searching [127].

We utilized query searching of PubMed,[1] the ACM DL,[2] and IEEE Xplore[3] to identify papers of interest. Our query had three categories, and within a category the "OR" condition was used, while between categories the "AND" condition was used. The first category utilized common keywords to describe disability;[4] the second used keywords to describe classification schemes;[5] the third used descriptors of motor abilities.[6] The search was over paper titles and metadata. These initial queries primarily identified literature that utilized existing measures of ability within their own research, but also identified literature that developed measures of ability. In the former case, the original source for the metric cited within the queried literature was accessed.

Along with identifying literature, our search identified how abilities are measured in different fields. These results helped define additional field-specific queries. For example, rehabilitation medicine utilizes terms such as “upper arm rehabilitation measures” or “gross motor function measures.” From here, we employed multi-level snowballing and reverse snowballing [93] to identify seminal papers, specific ability models, critical analyses of such models, and insights into how such models could be employed in ability-based design. We also identified themes and metrics from the Shirley Ryan AbilityLab Rehabilitation Measures Database [1].

Our final identified body of literature was separated into three areas that arose from themes we identified in the literature: (1) measures characterizing body mechanics, (2) measures describing quality of life and activities of daily living, and (3) measures of technology proficiency and use, which were largely from HCI. The literature from outside HCI, mostly in (1) and (2), was separated by how ability is viewed irrespective of field, as there is considerable overlap between fields for many of the metrics in how they are employed. This separation also highlights the two ends of a spectrum along which many fields view the body’s ability. Further, this separation also facilitates general translation to HCI, and helps to understand which measures could inform, or be adapted to, ability-based design. The following described measures are a representative sample of the measures identified in the literature. These measures were chosen to represent the range and diversity that motor ability occupies, the types of measurements available, and the prominence and acceptability of use.

## 3.1 Body Mechanics as “Ability”

Characterizing body mechanics is a fundamental method of measuring ability and is a common tool used to diagnose and track ability changes in fields such as medicine and rehabilitation [5]. Body mechanics can represent ability in multiple ways: directly as they are measured, indirectly as they are extrapolated to bodily function, or somewhere in between. In this subsection, we review the ways in which body mechanics can be used as measures of ability.

Body mechanics can be classified into descriptions of the positions of the body in static or dynamic conditions (kinematics), and the forces and moments that generate these positions (kinetics). Body position and movement are commonly measured through goniometers, motion capture, and inertial measurement units (IMUs). Body output forces and torques are measured through force plates, load cells, pressure sensors, and dynamometers. The generation of these forces and torques can be examined by proxy through tools that measure muscle activity, such as electromyography (EMG) [6].

The signals from these biomechanical sensors can be employed in computer systems to characterize motor control. For example, motion capture and other signals are employed in OpenSim and other musculoskeletal simulation tools to understand mechanisms of motor control [15, 97], or in the gait deviation index (GDI), an index of gait pathology for cerebral palsy [94]. One use of EMG is to calculate muscle synergies, or common motor modules of control [104], which can be used to calculate the dynamic motor control index during walking (Walk-DMC), a measurement that uses EMG to describe the variability of a user’s motor control while walking [103]. Indices such as the GDI or Walk-DMC can offer clinicians and researchers tools to understand the biomechanical impact of a disability as a numerical value.

These biomechanical signals can be used in two ways: (1) as *measures* of ability in assessments, or (2) as input to *control* computer systems [53, 89]. In the former case, biomechanical signals and the tools used to collect them are often utilized as measures to determine if someone falls with a “normal” range from a medical perspective. For example, using a system that tracks joint angles to identify range of motion is not clinically meaningful without a normative reference range for joint mobility. Such normative comparisons are considered necessary in medicine for diagnosis. For ability-based design, diagnosis or a comparison to “normal” is not the goal; thus, there is an expanded opportunity to use these metrics as purely observational values, ones to which computing systems might respond.

Clinicians often utilize physiological descriptors of how body mechanics might be altered or affected. These descriptors include topographic indicators, such as paraplegia or tetraplegia for cerebral

[1] https://pubmed.ncbi.nlm.nih.gov/
[2] https://dl.acm.org/
[3] https://ieeexplore.ieee.org/Xplore/home.jsp
[4] Keywords for disability: disability, impairment, ability.
[5] Keywords for classification: model, classification, system, assessment, scale, level.
[6] Keywords for motor abilities: motor control, motor, strength, ambulation, coordination, mobility, range of motion.

palsy (CP), spinal cord injury (SCI), and stroke, among others [29, 69, 78].

Many measures of ability describe information about body mechanics from a functional, non-task-specific perspective. These measures include range of motion, dexterity, strength, coordination, balance, and sensory function. For example, hand-grip strength, measured as a maximum voluntary contraction, is a common metric for monitoring sarcopenia [65, 68, 86, 99]. The International Standards for Neurological Classification of Spinal Cord Injury (ISNCSCI) by the American Spinal Cord Injury Association (ASIA) classifies SCI by the level of retained motor and sensory function after injury [87]. These levels are determined by examining sensation and muscle function within specific dermatomes and myotomes,[7] respectively. This information is used for the ASIA impairment scale (AIS) [69], a five-point letter-grade scale based on the Frankel classification of spinal cord injury [22].

Another assessment of body mechanics is the Fugl-Meyer assessment, a standard measurement tool to monitor stroke recovery as well as multiple sclerosis or traumatic brain injury [82]. It is a 226-point scale, with its items separated into five areas: (1) motor function, separated by upper and lower extremities, (2) sensory function, (3) balance, (4) joint range of motion, and (5) joint pain. Each item on the assessment is graded on a 3-point ordinal scale where 0 = "cannot perform," 1 = "performs partially," and 2 = "performs fully" [23, 29]. Such metrics that describe functional, non-task-specific ability, could be leveraged in ability-based design as generalizable metrics that translate across multiple activities.

Paralympic classification provides a substantial set of guidelines for functional classification of a body's abilities, as the aim is to minimize the disability's effect on the competition's fairness for the athletes [13]. Disability is separated into 10 types: muscle strength, range of movement, hypertonia, ataxia, athetosis, short stature, amputation, leg length difference, vision impairment, and intellectual impairment. Athlete assessments have evolved over time to use qualitative descriptions and quantitative ratio-based scales, and moving away from ordinal scales and ratings [107–109].

Other measures of ability in body mechanics include task-specific measures that are designed to be proxies of functional body mechanics. For example, the Box and Blocks test [66] and Nine Hole Peg Test [46, 67] capture hand and finger dexterity, respectively, through manual manipulation tasks. Similarly, the Action Research Arm Test (ARAT) describes grasp, grip, pinch, and gross movement [54, 131].

Furthermore, other metrics blend measures of body mechanics *with* bodily function during activities of daily living. For example, the Movement Disorder Society's Unified Parkinson's Disease Rating Scale (MDS-UPDRS) has four sections: non-motor aspects of experiences of daily living, motor aspects of experiences of daily living, a motor examination, and motor complications [33]. Further metrics that rely on activities of daily living alone are described in the next section.

In medicine, measures are commonly taken periodically to diagnose and assess changes in a person's body mechanics and function. Given the various ways that body mechanics can be measured, from body-worn sensors to clinical assessments, and from a fine-to-gross motor control, these measures lend themselves well to assessing motor ability by observing a range of biomechanical activities.

Holistically, the biomechanical view of ability could be considered "how a body functions." This locates ability directly in the body, and is less emphasizing of outcomes than ability-based design, which in its *ability* principle is focused on ensuring systems respond in some effective way to a user's abilities. Whereas this principle is system-focused, the biomechanical view of ability is more person-focused. It is not so much about a person performing to bring about a result in the world, but about a person's functioning as a property of the body itself. The implications for ability-based design are that, under the biomechanical view, ability is to be codified as functional capacity, almost independent of what that capacity can *produce* in the world. This may seem counterintuitive to the goals of ability-based design, in that ability-based systems are those that are meant to uphold what a user *can do*. However, systems that disregard the body's base functioning capacity ignore information about ability that is task-agnostic and therefore generalizable. Furthermore, this view of ability helps to emphasize that what a body *can do* need not always be performance based, but can also be about how the body comfortably exists in the world.

### 3.2 Daily Activities and Quality of Life as "Ability"

Instead of directly measuring motor function, another approach is to measure a person's ability to do activities of daily living and any symptoms or limitations present during such activities. These measures can either be through patient-reported outcomes or clinician observation. For example, the gross motor function classification system (GMFCS) and manual ability classification system (MACS) are both systems that describe gross—meaning overall—motor function for children with cerebral palsy [81]. These two motor ability measures are both five-level ordinal scales determined by clinician observation. The first scale, GMFCS, describes self-initiated gross motor function during and between everyday activities such as walking, standing, sitting, and any concurrent reliance on assistive devices for children aged 6–12 [76, 81, 129]. Palisano et al. [77] expanded and revised the GMFCS (as the GMFCS-E&R) to support kids aged 12–18 to better reflect the International Classification of Functioning, Disability and Health [75], and reflect both the patient's capability and performance and the influence of environmental factors. The second scale, MACS, is an upper-limb complement to the GMFCS that describes activities of daily living such as playing or dressing [17, 81].

Although the GMFCS and MACS are specific to cerebral palsy, there are also examples of tests that are agnostic to diagnosis. For example, the disability of the arm, shoulder and hand (DASH) questionnaire was specifically designed to be able to relate upper-extremity conditions by burden [35, 36]. The DASH is a 30 item questionnaire where each question is graded on a 5- or 7-point Likert scale. It includes questions that ask about a person's symptoms (pain, weakness, stiffness, tingling, numbness) as well as functional status (physical, social, and psychological) [36]. A shortened version of the DASH questionnaire, called QuickDASH, which contains 11 of the items of the original DASH, has also been developed [9].

[7] A dermatome is an area of the skin innervated by a segment of the spinal cord; a myotome is a group of muscles that are innervated by a segment of the spinal cord [69].

Instead of relying on patient reported outcomes or clinician observations, some ability assessments measure performance outcomes of activities of daily living. For example, the Jebsen-Taylor Hand Function Test times patients as they perform a variety of tasks [85]; however, the test has been shown to have poor correlation with patient-reported outcomes [14], calling its validity into question.

In contrast to the biomechanical view of ability, measures and metrics from activities of daily living (ADL) and quality of life (QoL) orient ability as an interplay between the body and the outside world. The biomechanical view of ability is isolationist; ability exists unchanged regardless of context or the world around it because it is located entirely in the body. By contrast, when ability is viewed through an ADL and QoL lens, it is drawn out of the body and located as an interplay of the body and the world. This blending aligns closer to the view of ability in ability-based design, especially with its treatment of so-called “situational impairments” [95, 121]. Furthermore, many metrics from ADL and QoL represent a subjective, first-person experience of ability. Indeed, many current examples of ability-based design take a performance-based view of ability (e.g., [84]), but ADL and QoL measures can help us to consider *why* performance may be altered and what effect on someone’s life it has. An ability-based system that integrates such measures could use this knowledge to better support their user in accomplishing everyday tasks.

### 3.3 Human-Computer Input Performance as “Ability”

The field of human-computer interaction (HCI) has developed many measures to quantify how people interact with user interfaces, whether digital or physical. These measures are often task-specific. For example, many measures focus on information transmission via pointing, including target selection speed, target selection accuracy, and Fitts’ law throughput [56, 58, 102, 132]. Text entry is also a canonical form of information transmission to computers, and metrics such as text entry speed [57], accuracy [100], and throughput [135] quantify input performance. Numerous additional metrics have been developed for text entry as well [3, 60, 101, 119, 134]. Similar notions of input efficiency have even been developed for brain-computer interfaces [128].

Fitts’ law [21] was first used as a model in HCI [12] to relate the time required to select a target to target size and movement distance in aimed pointing tasks. Different approaches have been taken to building Fitts’ law models, with details varying as to how experimental procedures are run, how pointing tasks are configured, and how regression coefficients are established [10, 39, 61, 70, 71, 102, 106, 126, 132, 133]. Further, of key importance is Fitts’ throughput metric [58], a form of information transfer rate (ITR), which unifies speed and accuracy as a measure of efficiency. (Similar constructs have been developed recently for text entry [135].) This view primarily holds that people’s abilities are measured by *input efficiency*. Although these measures were not necessarily created as explicit measures of ability, they are often used as such in HCI (e.g., [25]). Ability-based design itself had an early focus on pointing device performance for people with motor impairments [120].

Beyond quantifying efficiency in aimed pointing movements, other metrics in HCI provide descriptive statistics for how a user moves through space when selecting a target. Mackenzie et al. [59] established additional accuracy measures for mouse movement when selecting a target. These measures include movement variability, target re-entry, task axis crossing, movement direction change, orthogonal direction change, movement error, and movement offset. Keates et al. [45] extended these metrics for users with motor impairments, which were further built upon by Hawang et al. [38]. While the original intent of these metrics was to describe the dynamics behind overall pointing speed, accuracy, and efficiency [38, 45, 59], utilization of these movement metrics to inform system design has been shown to be beneficial for individuals with disabilities [122, 123]. This work presents a promising avenue for these metrics to represent ability in ability-based design.

Unsurprisingly, given the history of HCI, many of these metrics describe interaction with a pointing device and cannot always be applied to alternative input devices. For example, touch interactions unfold over time and space, and multiple touches can occur concurrently. Kong et al. [52] developed new metrics to quantify the time-varying behavior of touches given their non-instantaneous action and 2-D footprint. These metrics were inspired by those from MacKenzie et al. concerning mouse movement [59].

More recently, with the advent of ubiquitous computing, HCI has utilized sensors originally from biomechanics and health sensing to measure ability or accommodate situational impairments [121]. For example, accounting for perturbations in touchscreen typing while walking using accelerometers has shown to increase typing accuracy [30]. A similar correction was employed to measure and account for the effect of hand position while touchscreen typing [31]. Mariakakis et al. [63] detected inebriation using a combination of a phone’s built-in sensors and a small battery of human performance tasks on a touch screen that took about four minutes to perform.

These advances in ubiquitous computing have allowed for the monitoring and diagnosis of abilities. For example, motor manifestations of Parkinson’s disease (PD) were detected while typing on a touch screen [4] and on a keyboard [28]. These and other studies were described in an extensive review of remote assessments of hand function [34], which covered people with PD, stroke, multiple sclerosis (MS), spinal cord injury, and amyotrophic lateral sclerosis (ALS).

Individual efforts at employing ability-based design offer differing perspectives on how to characterize “ability.” Sarcar et al. [91] used models of tremor, dyslexia, and memory dysfunction for text entry performance on touchscreen devices to optimize keyboard key-size and the number of word predictions offered. Another approach to keyboard optimization utilized user-specific models of ability that incorporated how a user’s abilities might differ when moving in different directions to optimize keyboard layout [70, 71]. As noted, SUPPLE automatically generated user interfaces by representing a user’s pointing abilities as regression models that parameterized a decision-theoretic optimization process [25–27].

Alongside specific implementations of ability-based design, other implementations of user-specific modeling offer insight on how to measure and adapt to ability. For example, Findlater and Wobbrock [20] modeled a user’s keypresses to adapt the underlying classification model for a touchscreen keyboard. Hurst et al. [37]

detected users with and without pointing problems and predicted whether preventing accidental clicks and slips [105] would improve pointing issues.

Other systems take approaches that are about minimizing human error. For example, models of intelligence [40, 43] and psychomotor ability [42] have been used to optimize how a machine provides error correction and automation. These models were developed by assessing the motor control and ability to navigate a wheelchair by study participants.

Assessing a person's ability to interact with technology is also necessary to help prescribe interventions and assign assistive devices. As noted above, Koester et al. [47] built Compass, a software-based assessment tool for clinicians to measure desktop computer skills in order to select appropriate assitive interventions. On a smartphone, the SmartAbility app [118] maps abilities to specific assistive technologies based on user performance in a variety of tasks.

A highly apparent theme running throughout these metrics is how performance-oriented they are. Speed, accuracy, and efficiency are of primary importance where input devices and techniques are concerned. Indeed, this is not surprising for understanding "ability" in HCI, as pointing, text entry, and touch are pervasive and repetitive tasks. But such a view greatly limits a more holistic account of ability, even motor ability. People's abilities, even concerning computer use, extend well beyond their psychomotor task performance with input devices. Although ability-based design has been mostly applied in computing contexts (with some exceptions, e.g., [110]), it would benefit greatly from wider treatments of ability than just users' psychomotor behaviors. For example, cognitive, learning, and social abilities are highly relevant to computer use today.

Our extensive literature review has revealed that "ability" has primarily been characterized by biomechanical functioning, activities of daily living (ADL) and quality of life (QoL) issues, or human performance with computer input devices. Each of these views does indeed capture something about ability, but as to their use in ability-based design, the first and third tend to be overly narrow, while the second is overly broad and specific to everyday tasks. Something else is needed. We turn to this challenge in the next section.

## 4 DISTILLING "ABILITY" FOR ABILITY-BASED DESIGN

To organize the many metrics and measures presented above, we offer a framework for characterizing "ability." This framework establishes a robust concept of ability that represents its multiple facets, not just any one view encountered thus far. Indeed, this framework does not redefine any individual definitions of ability, but rather coalesces and synthesizes them. This framework is built of off conceptual user models that relate the *user*, *context*, and *task* [74]. Further, this framework is capable of representing multiple models of disability (e.g., social, medical).

Our ability framework is built of three axes: the *user* axis, *task* axis, and *context* axis. The *user* axis represents *who* is observing the metric, the *context* axis reflects the user's environment, and the *task* axis reflects the user's current situation. Each axis is defined by endpoints that reflect the span of the axis; the *user* axis extends from self-reported metrics to observed-by-others, the *context* axis spans metrics that represent internal to external context, and the *task* axis extends from task-agnostic to task-specific metrics. With this framework, any metric of ability can be placed inside the space created by these axes (Figure 1). Further, to represent "ability" in ability-based design, an interactive system should embody multiple points within this space, even aiming to occupy the extents of the three axes by employing multiple metrics.

These axes are grounded in work that relates *user*, *context*, and *task* [74], while also reflecting arguments that have been made to support multiple models of disability in HCI. Mankoff et al. [62] discusses flaws in models of disability, arguing that despite these flaws, these models still have their benefits, as long as they are working in concert with each other. The framework we have built to represent ability parallels this point, intertwining social, environmental, health, and other factors that compose ability and disability.

In addition, when utilizing this three-axis system, in order to reduce the burden on the user, one should aim to minimize the number of tasks the user must complete. In addition, when alternative metrics are available, one should limit the use of disease- and diagnosis-specific measures to limit the storage of personally identifiable information.

### 4.1 User Axis: Metrics that Reflect Different Points of View of the User

The *user* axis reflects the *who* is observing the user and spans from "1st person" to "3rd person." The first-person metrics are self-reported measures, while third-person metrics are observed by a third-party, whether that be a clinician, researcher, computer system, or other outside observer. Metrics that are composed of first-person and third-person data types fall between the two endpoints of the axis. Biomechanical measures, HCI input metrics, and wearable health data are some of the fundamental measures of ability that can exist along this axis. Among biomechanical measures, measures like the Fugl-Meyer assessment [23], which gives a complex understanding of both motor and sensory function, as well as range-of-motion and pain, would fit in the middle of the axis, as it is composed of both self-reported information and clinician observations. Instances of biomechanical metrics that fall towards the third-person end of the axis include wearable health data, obtained both in single instances and by continuous tracking. Additional consumer-facing signals could be heart rate and inertial sensing, signals common to most consumer smartwatches. Less common in consumer electronics, but under active investigation in HCI, are electromyography (EMG) measurements [16]. Quality of life metrics such as the disability of the arm, shoulder and hand (DASH) questionnaire [35, 36] and QuickDASH [9], populate the first-person end of the user axis, as they are reflections by the user.

Existing work in HCI that includes personalization, including implementations of ability-based design, provide thoughtful examples on how to marry personalized interaction with HCI metrics to create decontextualized measures that could exist along the user axis. For example, Mitchell et al. [70, 71] implemented an orientation-specific Fitts' law for each user in the design of their personalized keyboards. Similarly, Trudeau et al. [106] utilized Fitts' law to further examine differences in performance depending on orientation

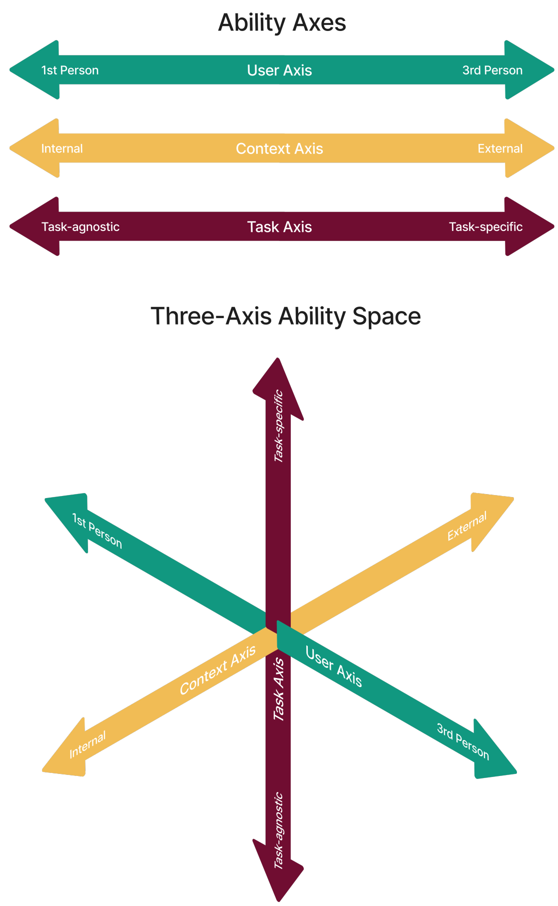


**Figure 1: Ability Axes as a three-axis space: the *user* axis, the *context* axis, and the *task* axis. The user axis extends from "1st person" to "3rd person," the context axis from "internal" to "external" contexts, and the task axis from "task-agnostic" to "task-specific." These axes are arranged to form a three dimensional axes space that represents ability.**

of the thumb when using a mobile phone. Taking into account the impact of movement orientation beyond just keyboards could help to build interfaces that are better suited to a user's abilities. Findlater et al.'s [20] personalized models for 10-finger touchscreen keyboard typing also shows how individualized input models could be leveraged in ability-based design. These examples highlight just a small portion represented by HCI input metrics to capture ability.

## 4.2 Context Axis: Context-Dependent Measures of Ability

The *context* axis captures ability measures reflecting the environment the the user is operating in. These environmental factors are both external and internal to the user [124]. Of the metric types that could fall along this axis, wearable health data and ubiquitous sensing data are especially pertinent, as well as quality of life measurements. This axis is organized on one end by measures that capture factors external to the user, while the other end is occupied by factors internal to the user.

Measuring external factors that are environmentally context-dependent helps to account for scenarios such as situationally induced impairments and disabilities (SIIDs) [95, 96, 121] as well as other disabling scenarios. For example, when walking, a user might have more errors due to movement or looking around at their surroundings that could be measured and corrected for [30, 72]. Alternatively, a device could sense when a user switches from using the device with two hands to one, perhaps due to needing to carry other objects at the same time [32].

Considering changes in ability that are internal to the user is also for the *context* axis. For many individuals with disabilities and chronic illness, there is significant fluctuation in ability or pain on a daily basis or even within a single day; being able to measure that is important [55, 130]. Accounting for these changes could be done specifically through wearable health data and feedback from the user. Although this end of the axis is user-centered, we chose to separate this from the user axis given the importance of considering the user's abilities not just on average, but in context.

## 4.3 Task Axis: Task-Dependent Measures of Ability

The last axis we consider for constructing our ability framework is the *task* axis. This axis is built to bring together the behaviors a user has during specific tasks when interacting with technologies and the many existing metrics that already describe these tasks. The two extremes of this axis are task-agnostic and task-specific. When considering where a metric might fall on this axis, it is important to consider whether it explains a user's ability to do a specific task or not. If the metric addresses a specific task, such as text input or an activity of daily living (ADL), it is task-specific. If a metric generalizes across tasks, it is still task oriented, but it would fall towards the middle of the axis. If a metric does not describe ability as an outcome or output, it is task-agnostic. While the importance of task-specific metrics is self-evident, also having task-agnostic metrics compensates for instances when task-specific metrics are not available and additionally provides a view of the user that is not only task- or outcome-oriented. For example, in the case of text input, only including text entry metrics for an application would fail to address how one might need to navigate between that experience and something else, whether an app or website.

Qualitative measures that reflect quality of life, as well as quantitative HCI input metrics that are not task-specific such as touch metrics [52], would fall on the task-agnostic end of this axis. The task-specific end of the spectrum would largely be occupied by HCI metrics such as text entry measures, as well as metrics that describe ADL. Metrics such as throughput and information transfer rate (ITR) would fall in the middle of the axis. This placement on the axis is because these metrics both have the ability to be task-specific as well as task-agnostic. ITR and throughput are specific to target selection tasks, but also can be generalized for tasks such as text entry.

Alone, these axes each provide unique ways in which ability can be represented. However, the true benefit of these axes lays in relating them to each other and representing ability as a multi-faceted concept. For example, to represent a user's ability with HCI text entry metrics, it is not just representing their ability as task-specific on the *task* axis, but also representing their ability as observable by a third-party on the *user* axis. The ability to generate text is also highly dependent upon the user's *context*; for example, the user could be walking at the same time they are generating text. Using only one metric that represents one point in the space of these axes fails to account for the complex nature of ability that is necessary for systems that implement ability-based design.

# 5 CONSIDERING PERSONAS FOR ABILITY-BASED DESIGN

To demonstrate the utility of our three-axis ability framework, we offer example personas as plausible fictions, which demonstrate how ability measures can be chosen to thoroughly occupy those axes (Figure 2). These personas show individual possibilities of the axes, and are not meant to represent the full extent and diversity of motor ability, but rather be illustrative of the utility of the axes. Additionally, the utilization of personas can be a helpful exercise for the implementation of ability-based design to successfully combine and consider users, contexts, and tasks. It is important to note that we use personas here to illustrate positions in our 3-D space, not as user caricatures that codify stereotypes or reinforce dominant preconceptions, for which personas as design instruments have been reasonably criticized [64]. To reinforce this caveat, we deliberately do not give our personas human names. Rather, think of them as points in our "ability space."

## 5.1 Persona Requiring Alternative Access

This persona requires alternative input access to use their tablet, alternating between access methods of switch-scanning and eye-tracking. They must alternate between these methods due to environmental conditions that do not permit eye-tracking or because of fatigue from eye-tracking. The most common task this persona uses their tablet for is composing text, whether emails, text messages, or documents.

To consider relevant measures of ability for this persona, we consider the axes of our framework both independently and together. Given that many tasks this persona performs are related to text entry, we would add a large number of text entry metrics to the *task* axis. These metrics are all fairly low-cost, both computationally and in terms of the effort needed to integrate them into a computer system. For the *context* axis, we could consider internal context, specifically fatigue, as this persona fatigues from use of the eye-tracker. While user fatigue could potentially be measured directly by observing how movement patterns of their eyes change, we also could use task-specific metrics to observe fatigue. Finally, for the *user* axis, we could look at metrics that could quantify the user's motor abilities such as their dexterity and spasticity. These motor abilities are considered so that during use of their switch scanner, the system can understand how often accidental selections occur.

We can also go beyond this persona's use case to consider more individuals that use alternative inputs to access their technology and how their tasks and contexts differ. Beyond utilizing text entry metrics, we could look at more general HCI metrics such as target selection speed, target selection accuracy, Fitts' law throughput [56, 58], and information transfer rate [128]. These metrics fit a variety of both tasks and contexts. We can also consider a user that only sometimes uses alternative access, for example, someone that alternates between using a tablet with touch and switch-scanning. In this case, we can use touchscreen metrics [52] to monitor fatigue during touch prior to the user changing to switch-scanning.

## 5.2 Persona with Limited Fine Motor Control

This persona has Parkinson's disease, resulting in limited fine motor control. Her primary interactions with technology are for communication purposes; she frequently calls, video-chats, and texts her family and friends. She will often receive pictures and videos that she likes to save for future reference. However, this persona has difficulty navigating these tasks at times due to her tremor. It is time-consuming for her to compose a text message, and sometimes she will give up and call instead, even if it is inconvenient. Sometimes she will also decline a call that she meant to accept due to her tremor. She has found adaptations by using a voice assistant, but she is not entirely happy with this solution.

How might we go about characterizing the abilities of this persona using our framework? Similar to the first persona, we can consider a large number of text entry metrics for the *task* axis [3, 100]. In addition, we can add general non-task-specific metrics, such as touch metrics [52]. Given that this persona has Parkinson's disease, we can consider metrics for the *user* axis, such as Movement Disorder Society's Unified Parkinson's Disease Rating Scale (MDS-UPDRS), which contains components along the user axis, given it's reflection of both quality of life and motor movements. Considering the *context* axis, we look at both external and internal factors for this persona. Individuals with Parkinson's disease often have daily fluctuations in ability, especially as medication wears off [83]. Furthermore, the motor manifestations of Parkinson's disease might not be symmetric [88], and so her ability to do tasks could vary significantly by which hand she was using to hold the phone and use it. These symptoms are why it would be important to consider onboard sensing to determine her grip pattern.

Expanding this persona to additional devices, one could consider factors for the context axis, such as device-specific measurements. For this persona, such device-specific measurements would translate to input-specific measurements, for example, in the case of a desktop computer controlled by a mouse, measuring jitter. Expanding to other diagnoses beyond Parkinson's, including the case in which there is no diagnosis, one could add metrics to the user axis such as disability of the arm, shoulder and hand (DASH) [35, 36] or the shortened version, the QuickDASH [9].

## 5.3 Persona Experiencing a Movement-Induced Situational Impairment

This persona works at home two days a week and the other days works in an office. When she works in her office, she commutes by bus and on foot. During her bus commute, she often reads books she has downloaded onto her phone. Sometimes while on the bus she answers emails, especially if she is running late. Only occasionally

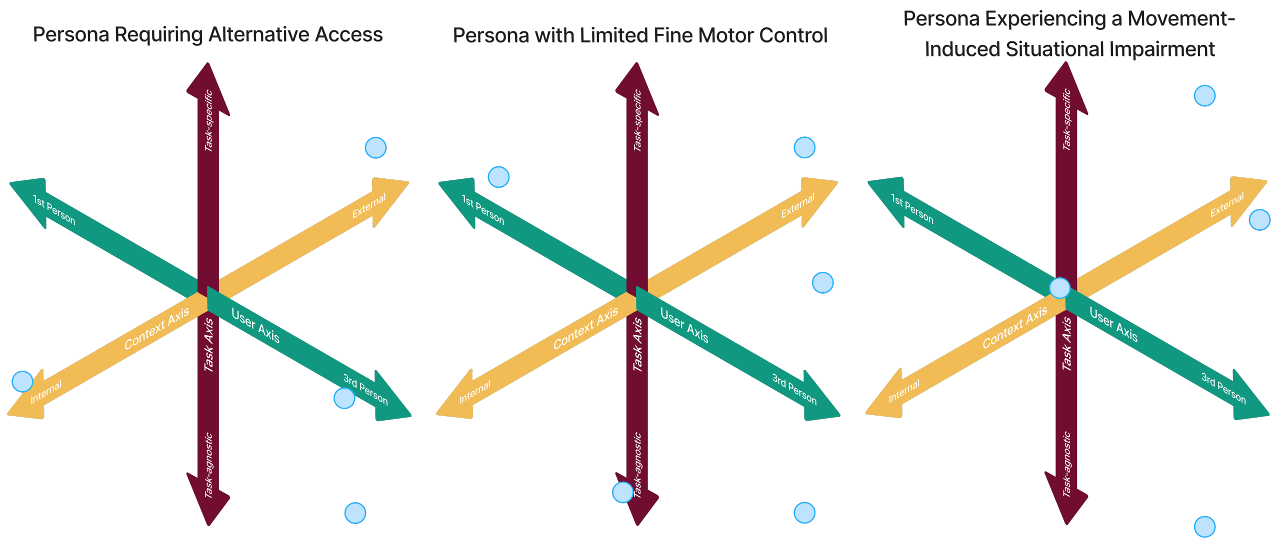


**Figure 2: Example personas demonstrating how metrics to describe ability occupy the extents of the ability axes.**

will she answer emails while she is walking to or from the bus. On days that she is working from home, she often will take phone calls while she is on a walk. During this time, she will sometimes have to look at her phone to reference an email or her calendar.

To start constructing metrics around this persona, we first consider the *context* axis, given that she is using her phone under multiple different environmental conditions that will all influence her ability to operate the phone accurately. The phone's onboard sensors can measure acceleration and rotation whether due to the movement of the bus, or the user's movement while she is walking or handling the phone. If she is wearing a smartwatch, its onboard inertial sensors can further be utilized to anchor the phone's movement and differentiate between *her* moving the phone and the *environment* moving the phone. These measurements for the context axis play into the *task* axis, as having highly precise movements matter more when the user is composing an email as opposed to when she is reading.

For the tasks she does, we would consider text entry metrics [3, 119]. We additionally consider more general metrics that reflect the user's ability to operate her phone, specifically touch metrics [52]. In the case of a user such as this persona, we would rely less on the *user* axis, especially as she would have fewer, if any, clinical metrics relevant to her.

Expanding beyond this persona to a more general persona under a movement-induced situational impairment, we could utilize clinical metrics that fall along the user axis, especially those relevant to the effects of motion. For example, these metrics could reflect a person's proneness to fatigue as they walk or those who have limited fine motor control, as individuals with limited fine motor control would have even more difficulty composing emails on a bus with extraneous motion.

## 6 DISCUSSION

Our literature review uncovered three general ways that "motor ability" has been characterized: by one's biomechanical function, by activities of daily living (ADL) or quality of life (QoL) issues, and by use of input devices in human-computer interaction (HCI). All three of these characterizations were limited in significant ways, but taken together, they informed a rich perspective on ability.

Leveraging the above notions of ability, our three-axis ability framework for ability-based design consisted of the *user*, the *context*, and the *task*, enabling us to consider numerous metrics for characterizing "ability" for our personas. We organized this axis space to reflect current work in ability-based design [124] as well as conceptual user modeling [74]. These axes are also designed to be set together as a three-dimensional space to indicate that these considerations cannot be fully separated when modeling ability. We include Table 1, which details each metric we reviewed, explaining where in the three-axis space it sits.

The extents of each axis were chosen to represent a range of abilities. For the *user* axis, choosing both qualitative and quantitative measures of ability allows for both unbiased measurements as well as the user's perspective on their abilities. To this latter point, we stress that any system that uses ability-based design must reflect a user's abilities as the user sees them, not just as they are computationally assessed. For the *context* axis, we chose the extents to be internal and external. This choice was in view of literature that argues for the importance of designing to account for natural variations and fluctuations in abilities (internal contexts) [55, 124] as well the social model of disability (external contexts) [98]. Finally for the *task* axis, we chose extents that allowed the axis to reflect the wide variety of metrics that are available for use. Many of these are not task-specific or directly translate to activities involved with

**Table 1: Measures of Motor Ability and their Categorization**

| Measure | Assessment Method | Axis Location | | | References |
|---|---|---|---|---|---|
| | | User | Task | Context | |
| Body Mechanics | Computer Systems | 3rd Person | Midpoint | Midpoint | [5, 6, 15, 53, 89, 94, 97, 103, 104] |
| | Clinician Observation | 3rd Person | Midpoint | Midpoint | [29, 69, 78] |
| Functional Body Mechanics | Computer Systems | 3rd Person | Midpoint | Midpoint | [46, 65–68, 86, 99] |
| | Clinician Observation | 3rd Person | Midpoint | Midpoint | [22, 23, 29, 69, 82, 87] |
| ADL | Clinician Observation | 3rd Person | Task-specific | Midpoint | [14, 17, 76, 77, 81, 81, 81, 85, 129] |
| QoL | Self-reported | 1st Person | Midpoint | Midpoint | [9, 35, 36] |
| Target Selection | Information Transmission | 3rd Person | Midpoint | Midpoint | [56, 58, 58, 102, 132] |
| | Movement Patterns | 3rd Person | Midpoint | Midpoint | [38, 45, 59] |
| Text Entry | Efficiency | 3rd Person | Task-specific | Midpoint | [3, 100, 119, 135] |
| Touch | Movement Patterns | 3rd Person | Task-agnostic | Midpoint | [52] |
| Situational Impairments | Movement Patterns | 3rd Person | Midpoint | External | [30, 31, 121] |
| Disease Monitoring | Movement Patterns | 3rd Person | Midpoint | Internal | [4, 28, 34] |

technology, yet they reflect vital perspectives such as the user's perceptions of their abilities.

These axes reflect the interplay of different models of disability stressed by other researchers in HCI. Mankoff et al. [62] and Mack et al. [55] both emphasized the balance between medical and social models and how each can describe different aspects of ability and disability. The design of our axes also opens up the possibility to use various metrics from a new perspective. For example, while many of the metrics we described were clinical, such metrics could be employed under contextual factors to describe natural internal fluctuations or external environmental factors as well.

With these axes in view, practitioners of ability-based design should be able to maximize coverage over the axis space to create systems that are robust to users' abilities, both objective and subjective, translatable, yet specific across devices, contextualized to the task at hand, and robust to external environmental conditions and changes in a user's abilities.

Although we specifically address metrics that measure motor abilities for the scope of this paper, there are other measures of ability that influence motor ability, yet are not direct measures of motor ability itself. For instance, the ability to access medication that improves tremor from Parkinson's disease is a contextual measure of ability. We therefore must also consider larger environmental, contextual, and social metrics when considering motor ability to avoid creating systems that are not representative of users.

Furthermore, our framework's axes represent how ability can best be represented *in* an interactive system. Ability is, in reality, an incredibly complex concept, one for which individual metrics do not—and never can—fully encapsulate the lived experiences of the individual they are characterizing. But the more our computing systems can accurately understand our abilities, the more responsive they can be to accommodating them.

### 6.1 Limitations

A limitation of this work is that it only considered users' motor abilities. We incurred this limitation when building our framework for ability-based design given the myriad metrics that represent motor abilities. Our belief is that given the wide variety of metrics that this infrastructure supports, the framework would be translatable to other types of abilities. Additionally, these axes could help support the identification of new metrics to fill out the axis space for these other ability types (e.g., cognitive, sensory).

This work stops short of actually implementing an interactive ability-based system using our ability framework. Rather, we chose to focus on our extensive literature review and synthesis to emphasize that HCI can integrate metrics from other fields for ability-based design. Our three axes are also generally supported in literature as ways to model users [74], and so there is a strong foundation for structuring these axes as we did.

Finally, this work focuses on the measurement of ability to aid the implementation of ability-based design. We recognize that this aspect is only one facet of the implementation of ability-based design; design process is another, unaddressed here. Furthermore, measuring ability, especially using clinical tools, leans towards the medical model of disability; we juxtapose that with the *context* axis that discusses metrics from the social model of disability [62, 98].

## 7 FUTURE WORK

This work outlined a framework for characterizing "ability" for ability-based design, but did not exercise the framework in an end-to-end design process through implementing an actual ability-based system. We leave such an endeavor for future work. Doing so would enable us to consider the framework and its many metrics for possible inclusion in a working system, and to assess the "coverage" of the three-dimensional space of the framework by the metrics under consideration.

While this work highlighted the move from implicit notions of ability to concrete notions of ability for motor ability, we envision that the framework we developed will extend to disabilities beyond motor disabilities. We hope future work explores this transition for other disabilities and furthermore, implements systems using this framework for other disabilities.

The integration of clinical metrics into ability-based systems raises privacy concerns that are not present in systems that rely solely on traditional HCI metrics to capture ability. Systems that use these metrics will need to adopt security practices that ensure proper storage and access of this information and additionally ensure the user feels at ease with volunteering such information. Furthermore, future work could investigate the correlation between measures of ability outside of HCI to measures from within HCI so that these HCI measures could act as proxy measurements. Finding correlations could enable a system designer to reduce any reliance on clinical metrics that have patient-sensitive information. Moreover, HCI-specific metrics showing high correlations with clinical measures would allow for more metrics to be accessible to those that have difficulty obtaining a clinical assessment [47, 48].

## 8 CONCLUSION

Current implementations of ability-based systems offer unspoken or piecemeal approaches to defining and measuring ability, *the* central concept in ability-based design [124, 125]. To erect a unified framework for characterizing "ability," we reviewed measures of motor ability from the fields of rehabilitation, occupational and physical therapy, medicine, biomechanics, HCI, and more. We described the approaches these metrics take to measuring ability and organized these metrics into a three-axis framework for ability-based design. These axes are the *user* (from 1st person to 3rd person), *context* (from the user's internal context to the environment's external context), and finally, the *task* (from task-agnostic to task-specific). We also provided example personas that utilize metrics that occupy this three-axis space to demonstrate the utility of the axes. It is our hope that by characterizing "ability," the creation of ability-based systems can be more informed, inclusive, and successful.

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