'Are They Doing Better In The Clinic Or At Home?': Understanding Clinicians' Needs When Visualizing Wearable Sensor Data Used In Remote Gait Assessments For People With Multiple Sclerosis

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ABSTRACT

Walking impairment is a debilitating symptom of Multiple Sclerosis (MS), a disease affecting 2.8 million people worldwide. While clinicians' in-person observational gait assessments are important, research suggests that data from wearable sensors can indicate early onset of gait impairment, track patients' responses to treatment, and support remote and longitudinal assessment. We present an inquiry into supporting the transition from research to clinical practice. Co-design by HCI, biomedical, neurology and rehabilitation researchers resulted in a data-rich interface prototype for augmented gait analysis based on visualized sensor data. We used this as a prompt in interviews with ten experienced clinicians from a range of MS rehabilitation roles. We find that clinicians value quantitative sensor data within a whole patient narrative, to help track specific rehabilitation goals, but identify a tension between grasping critical information quickly and more detailed understanding. Based on the findings we make design recommendations for data-rich remote rehabilitation interfaces.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; **Empirical studies in interaction design**.

KEYWORDS

multiple sclerosis, gait assessments, remote care, transition to clinical practice, data visualization, wearables

ACM Reference Format:
Ayanna Seals, Giuseppina Pilloni, Jin Kim, Raul Sanchez, John Ross Rizzo, Leigh Charvet, Oded Nov, and Graham Dove. 2022. 'Are They Doing Better In The Clinic Or At Home?': Understanding Clinicians' Needs When Visualizing Wearable Sensor Data Used In Remote Gait Assessments For People With Multiple Sclerosis. In *CHI '22: ACM CHI Conference on Human Factors in Computing Systems, April 30 - May 6 2022, New Orleans, LA.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3491102.3501989

1 INTRODUCTION

Multiple sclerosis (MS) is a chronic autoimmune, inflammatory neurological disease of the central nervous system (CNS). It is the most common progressive CNS disease in young people [36, 38], affects 2.8 million people worldwide [109], and research suggests a prevalence rate of more than 900,000 adults in the US alone [107]. Up to 85% of MS patients can experience walking impairment, making this one of the disease's most frequent and debilitating symptoms [64]. As a result, assessing changes in a patient's gait has become a crucial metric in routine clinical evaluations for MS. Characterizing MS patients' gait impairments has typically been achieved through in-person observational studies and simple walking tests, such as a timed 25 foot walk [71, 92]. More recently, research has suggested that quantitative approaches to gait analysis that use wearable inertial sensors [85] offer a useful tool that allow for assessment under more ecologically realistic conditions, especially in mild to moderate cases. Similarly, studies in which triaxial-accelerometers have been used to quantify day-to-day physical activity in patients with mild Parkinson's Disease, show that continually monitoring activity can help clinicians verify the effectiveness of rehabilitative treatments [89]. This suggests that augmenting observational assessments with data from inertial sensors contained in consumer

CHI '22, April 30 - May 6, 2022, New Orleans, LA

ACM ISBN 978-1-4503-9157-3/22/04…$15.00
https://doi.org/10.1145/3491102.3501989

wearables may help clinicians to identify the onset of gait impairment more quickly, and track whether a patient is responding to proposed treatments more effectively. Beyond this, wearables also offer opportunities for remote and longitudinal assessments, and a potential window onto how CNS diseases impact patients on a day-to-day basis.

However, despite the apparent benefits of evidence-based practices (EBP) which build on these innovations, the translation from biomedical research to clinical practice remains challenging. Estimates suggest only half of new EBP are ever widely adopted [8], and that the average time-to-adoption of those that are can be as much as 17 years [79]. Moreover, with biomedical research into the use of digital technologies, such as using body-worn sensors to quantify and standardize assessment measures, there are likely additional barriers to adoption [41, 55, 76]. One reason for these barriers may be a shift of focus towards data, which can impact the roles of healthcare workers [15]. This paper reports on an ongoing collaboration between HCI, biomedical, neurology and rehabilitation researchers to design interfaces that support MS clinicians' practice by visualizing gait analysis data that has been generated by a commercial sensor attached to a patient's shoes. These wearable inertial sensors are typically used to help athletes better understand their running action, and this paper explores their utility in supporting MS monitoring and assessment.

In an iterative process involving multiple stakeholders we designed a data-rich interface prototype for augmented gait analysis based on visualized sensor data. We recruited 10 experienced clinicians for interview, with participants representing a variety of roles in clinical and rehabilitation disciplines, including physical therapy, nursing, and neurology. We probed on clinicians' current work and presented them with a low-fidelity prototype interface, which acted as a design prompt to probe questions of future work and elicit ideas and requirements. Our qualitative analysis of data from these interviews provides the basis for identifying design opportunities and recommending design guidelines. The remainder of this paper is structured as follows. Next we describe the context in which this research was conducted. We then discuss related work. Following this we present our research method and describe in detail the interface prototype we used as a design prompt during practitioner interviews. We then present our findings, which we discuss in light of prior research accompanied by design recommendations for data-rich remote rehabilitation interfaces.

1.1 Contributions

This paper contributes to HCI research in the context of support for clinical rehabilitation practitioners through inquiry into the design of data-rich interfaces that visualize detailed biomechanical metrics gathered remotely and longitudinally using wearable sensors. In particular, we investigate how data from shoe-worn sensors might be integrated into the practices of clinicians treating patients with MS and similar neurological conditions. Specific contributions include:

- An introduction to biomedical research in which wearable sensors are being used to develop cutting-edge evidence-based clinical practice, an application of sensor technology that should be of interest to many in the CHI community.
- A qualitative analysis of interviews with experienced clinicians that helps to characterize different clinical challenges, and explores how the potential benefits of new evidence-based practices enabled by wearable sensors might be integrated into future practices.
- A set of design recommendations for visualizing biomechanical metrics derived from wearable sensor data, which are centered around supporting clinician needs and easing the adoption of evidence-based practice.

2 RESEARCH CONTEXT

As part of a wider inquiry into how digital technologies might shape possible future healthcare work, this study aims to identify design opportunities to support emerging EBP. We report on a collaboration between HCI, biomedical, neurology and rehabilitation researchers, which investigates new approaches to monitoring and managing the symptoms of neurological conditions, such as MS. The paper introduces a design of an interface to visualize data from shoe-mounted consumer wearables in ways that support the varying practices of clinicians within our university's MS Comprehensive Care Center. This design inquiry aims to help introduce new EBP that research using the wearable sensors enables, and support its adoption. We report on interviews with clinical practitioners that help us better understand the practice context of different MS clinicians (e.g., neurologists, nurse practitioners, physical therapists). During these interviews, participants were introduced to a low-fidelity interactive Figma [1] prototype, which we used as a design prompt by asking them to complete a series of exploratory tasks and 'what if' scenarios. This prototype, and the tasks and scenarios we explored with participants, resulted from co-design activities undertaken by the research team.

2.1 Gait Assessments in MS Rehabilitation

Ambulation is the ability to walk without assistance, originating from a complex pattern of electrical signals in the central nervous system successfully sent along the nerves to activate and coordinate muscles. The clinical assessment of ambulation provides key metrics that help predict health status and functional decline [43]. Walking impairment is a clinical hallmark of MS, resulting from a combination of multiple disease-related factors such as muscle weakness and spasticity, sensory impairment, and cerebellar dysfunction [39]. Reduced mobility due to gait dysfunctions occurs in up to 85% of people with MS, leading to life-altering consequences [64]. Even subtle changes in walking can indicate ongoing disease activity and progression, and therefore the potential benefits of early intervention make gait assessment an important part of routine clinical evaluations in people with MS. Evaluation typically involve clinicians' observation with qualitative descriptions of any deviations and compensatory mechanisms, which may be completed with ratings on standardized scales, e.g. Hauser Ambulatory Index (AI) [50] and Dynamic Gait Index [99]. These evaluations typically include the timed 25 foot walk test [12]. Assessment may also include self-report inventories for patients to directly rate their own walking functions. While these tests and scales are inexpensive and require only limited training, they are also prone to evaluator

[1] https://www.figma.com/

variation (e.g., inter-rater reliability, intra-rater reliability) and can be difficult to compare across multiple measurements. They may also be less sensitive to subtle changes at early-stage disease [98].

2.2 Digital Technologies in Quantitative Gait Analysis

Recent developments in sensors and motion capture has enabled researchers and clinicians to investigate biomechanical parameters such as kinematics, kinetics, muscular activity, and plantar pressure distribution, and develop new approaches to quantitative gait analysis that can detect pathological patterns at early disease stages [80, 86]. These approaches can also enable comparisons of a particular patient's performance, e.g. relative to normative data or pre vs post clinical intervention. Furthermore, they can support greater degrees of standardization and automation, and reduce confounds introduced during human-supervised assessment [85]. Introducing quantitative assessment enabled by digital technologies can augment qualitative clinical evaluations by offering accurate, repeatable, and reproducible gait measurements, and help provide insight into neuromechanical factors that underlie impaired gait in patients with MS [40]. The development of wearable sensors also presents opportunities for remote health monitoring and assessment during day-to-day activities, which can inform clinical decisions [105]. This is beneficial because the way a person walks while under observation completing a short task within a clinical evaluation is unlikely to accurately reflect all of the variation in how they walk in the differing circumstances of their real-life situations. This may also enable clinicians to detect small changes in gait kinematics that help identify within-day fluctuation, and determine the range of variation in temporal and spatial gait features underlying the pathological processes responsible for disease progression. In this way, wearable sensors and other digital technologies can contribute digital biomarkers [7] to help monitoring clinical disease activity and assess the efficacy of symptomatic and rehabilitation therapies.

Investigators at our university's MS Comprehensive Care Center are developing a new protocol for accurate remote gait assessment. This protocol utilizes Runscribe [2] a commercial 9-axis motion sensor system, which is validated with gait measurements taken during an in-clinic baseline assessment visit using an independently validated inertial motion system [3]. Patients complete an initial gait assessment during a routine outpatient visit, and are provided with the shoelace-mounted sensors. They are then trained in setting up and positioning the sensors, connecting to the system's smartphone app, and in completing an at-home walking test. In addition to data collected during scheduled telemedicine visits, this protocol also supports asynchronous and longitudinal assessments by collecting and storing data such as gait velocity, stride length, and stride angle, based on independently completed tasks repeated on a daily or weekly basis. From a clinical perspective this remote health assessment enables meaningful real-world mobility measures to be collected. However many questions remain open with regards to appropriate methods of data visualization to support clinicians' analysis and interpretation. This paper describes our design-focused research into how best to present the data this protocol offers to clinical practitioners in a variety of roles.

[2] https://runscribe.com/

[3] BTS Bioengineering G-Walk

2.3 Designing an Initial Prototype to Help Elicit Clinicians' Perspectives

Our aim in this research has been to investigate how the detailed, remote, and longitudinal gait analyses facilitated by wearable sensors, which research suggests offers opportunities for new examples of evidence-based clinical practices, might be integrated effectively with clinicians' current work. Because these analyses and the data they are built on are most likely unfamiliar, we built an initial prototype that could act as a design probe during interviews. The development of this prototype followed an iterative process of collaborative design between members of the research team. During this process HCI researchers, led by the first author, worked to reimagine how the biomedical research of the second author might be presented according to visualization best practices. Over a year-long period we met on a weekly basis to share and test ideas, and conduct informal user testing. This included evaluation sessions with co-authors, including experts in rehabilitation medicine and clinical neuropsychology, and with clinical members of the wider project this research is part of.

As an example of this process we describe developments from our initial data visualization sketches which consisted solely of a spider plot and a boxplot. When these were presented to our clinical partners they suggested that in their experience physicians would benefit from an overview that could be quickly grasped. Building on this feedback, we refined the design and added initial interactivity. We also built on lessons from prior research that implements visualizations for longitudinal assessments based on daily averages, and which include tools that allow clinicians to explore possible causes of changes in gait, e.g. [3, 4, 82, 106]. This updated version included a heatmap showing longitudinal data that was color-coded to enable users to see at a glance improvement or regression in a patient's gait, which was based on feedback we received from clinical partners that assessments and comparisons to population norms were easier to process in this way than using a line chart. Further feedback from clinician partners highlighted potential challenges in differentiating between a patient's right and left foot, and asked for refinements to improve the spider plot's understandability. This led to a monochromatic color scheme for left and right foot identification. Following this feedback we also added color indicators for gait deviation and support for direct interaction with visualization elements to access additional information. At this stage, the prototype was also adjusted to align with accessibility guidelines and adopt a color-blind-friendly color scheme. User testing with clinicians in our wider team helped inform updates to the interface design that connected changes in patient data to important clinical events, such as medication and physical therapy. Our final round of informal evaluation aimed at gathering insights into medical usefulness, and included user testing sessions with authors 5 and 6 in which we additionally prototyped our interview protocol. Feedback led to usability improvements, and changes in the language and terminology that made these more clinician-friendly. The prototype that emerged from this highly iterative process, and that was used as a probe in our clinician interviews, is described in detail in section 4.3.

3 RELATED WORK

This study bridges 2 main areas of HCI research in healthcare. First we discuss literature that relates to the introduction and adoption of new digital technologies in clinical settings. Here we present an overview of the general challenges faced, before focusing in on electronic health records (EHR) and considerations associated with visualizing healthcare data. Second, we discuss literature presenting research into the use of wearable sensors to support rehabilitation healthcare.

3.1 Implementing Healthcare Technologies

Information technology, such as telehealth systems, plays an increasingly critical role in healthcare. However, one of the key challenges to introducing new systems is whether clinicians and other healthcare workers will fully adopt and accept them, together with the potential changes to current practice they may bring. May [75] highlights the importance of meso-level factors, including user-centeredness and realism in the design, implementation, and evaluation of new modes of healthcare, as being important to this process. Bernstein, McCreless, and Cote [11] also highlight the significance of end-user involvement and additionally suggest the role of supportive leadership as critical factors. Poon et al. [88] highlight financial resources and incentives; while Lin, Lin, and Roan [69] identify perceived threat and perceived inequity as key barriers for clinicians. Gagnon, Ngangue, and Payne-Gagnon [44] suggest that factors including perceived usefulness and ease of use, cost, time, privacy and security issues, as well as familiarity with technology are important areas of concern. Pai and Huang [84] suggest that perceptions of quality are mediated by perceived usefulness and perceived ease-of-use, and influence intention to use. Using Davis' Technology Acceptance Model (TAM) [28, 29] Ketikidis et al. [59] found no significant differences in likely acceptance between nurses and medical doctors, and highlight education and organizational culture as important in promoting adoption. Strudwick [103] recommends modifying TAM questions for specific contexts, e.g. in order to better understand the factors that influence adoption in nurses; while Gagnon et al. [45] suggest that the perception of facilitators is the most important variable to consider for increasing doctors' and nurses' intention to use the new technology. To improve the likelihood of acceptance, Clark and Kelliher [26] describe integrated personal, economic, and regulatory issues for designers of telehealth systems to consider, and propose guidelines for areas such as therapist and patient trust.

3.1.1 Electronic health records. One area in which healthcare technology has been widely implemented is electronic health records (EHR), which contain a history of patient medical data. Bowens et al [16] suggest that successful integration into clinical workflow will increase adoption; while Hsu et al [54] highlight the challenges and potential applications of leveraging disease models to improve integration and interpretation of clinical patient data. Christensen et al [24] investigate the potential impacts of these systems on clinician-patient relationships, and suggest that better understanding of existing paper records will help improve EHR. Similarly, Bossen et al [14] study existing use of paper-based medical records in order to understand how clinicians gather information. However, Jensen et al [57] suggest that EHR systems face widespread non-use; and studying how electronic patient notes are used, Brown et al [19] note that clinicians directed little attention to medication lists, vital signs or laboratory results compared with the impression and plan section. Different conceptual frameworks have been proposed to help mitigate the potential challenges to widespread adoption of EHR systems, these include Feblowitz et al [37] who focus on understanding clinical summarization in computer-independent and computer-supported clinical tasks; Hirsch et al [52], who offer a patient summarization and visualization tool; and Bashyam et al [9] who focus on simplifying the information retrieval and discovery process necessary to make an informed diagnosis. Other suggestions for improving EHR and their uptake include, facilitating clinicians' rapid-detailed narrative observations [58], integrating graphical devices and natural language processing [48], structuring and visualizing medical data to promote an evidence-based approach to overcoming difficulties in interpreting and reviewing disease progression [53], and problem-centric visualizations organized around medical conditions [20].

3.1.2 Visualizing Healthcare Data. Patient medical data often consists of large amounts of very text-heavy information, and successfully presenting this data is a key challenge for technology adoption in healthcare. For example, Sultanum et al [104] present design guidelines for healthcare visualization that include the need to make text central to visualization design and supporting situational awareness. Similarly, Le et al [65] offer guiding themes that include focusing on the perceived level of detail and considering the application of visual displays. West et al [113] address barriers to using patient-generated data in clinical settings, including challenges to data presentation that highlight potential differences in the way patients and clinicians might respond to visualized data. Zhang et al. [118] seek to improve the usability of EHR through visualizing their data using a metaphor based on the common 5Ws narrative building tool, leading to reduced time and effort accessing information for diagnosis. Similarly, Wang et al. [110] also aim to improve EHR through visualization, displaying patient histories aligned on sentinel events. Other proposals for novel visualization of healthcare data include, designing genealogy graphs to support medical researchers' understanding of multifactorial diseases [83]; visualizing event flows for quality control [115]; helping doctors devise care plans based on outcomes from clinically similar patients [87]; and incorporating patient generated data into clinical consultations [61].

Dashboards are one of the most common use cases for data visualization, and increasingly used for sharing information across roles, domain expertise and motivations both within and across organizations. Sarikaya et a. [93] offer a review of dashboard design and purpose, suggesting that reflecting purpose and context is a key challenge for designers armed with a limited data and representation vocabulary. Elshehaly et al. [34] present a tool for generating and dynamically configuring visualization dashboards for healthcare quality improvement, with the aim of increasing dashboard adaptability. Beyond dashboards, narrative visualization [33, 94] is suggested as an approach to visualizing psychological

Table 1: Overview of interview participants.

Participant ID	Clinical Role	Experience
P1	Nurse practitioner at university hospital	22+ years
P2	MS adult & pediatric fellow at university hospital	5+ years
P3	Program manager of outcome management, co-chair of performance & quality improvement at university hospital, practicing physical therapist from 2005-2018	13+ years
P4	Researcher of new technologies in rehabilitation at a research and development firm	5+ years
P5	Physical therapist in vestibular rehabilitation at university hospital	15+ years
P6	Neurologist at university hospital, assistant professor of neurology	12+ years
P7	Physical therapist, clinical practitioner, professor in physical therapy department	50+ years
P8	Overseer of all therapy services at university hospital	19+ years
P9	Director of physical therapy at university hospital	24+ years
P10	Clinical affairs manager & researcher in lower limb products at a research and development firm	13+ years

aspects of healthcare data [100], and the temporal trends of patients' clinical records in the context of home healthcare [74]. An alternative to this is to approach healthcare data visualization by considering the context of individual conditions, e.g. communicating possible prostate cancer outcomes [47] or temporal aspects of stroke patients' treatment [70].

3.2 Wearable Sensors for Rehabilitation Healthcare

Recent research has investigated how sensors, such as wearable inertial measurement units (IMU), might play a role in rehabilitation practices including those for MS. For example, Chen et al [22] offer a review of current techniques for gait analysis used inside and outside clinics, and propose key evaluation metrics, including swing time, double stance time and stance phase time. Zhu et al [119] suggest that healthcare professionals should respond to challenges regarding heterogeneity, exhaustive assessments, frequent tailoring, and adherence; while needing support for assessment and adherence using meaningful and reliable at-home data. Suggested benefits for such approaches include, precision [1], unobtrusive privacy [81, 97], and the potential to identify subject-specific changes [63]. Other systems that focus on monitoring and visualizing gait metrics in particular include Wang et al [111] who offer gait trajectory reconstruction and visualization methods targeting hemiparetic gait patterns, and Wu et al [117] who investigate walking patterns for real-time gait monitoring using an inertial shoe-based sensor. Anwary et al [6] focus on low cost, portability, and easy of use for at home or in-clinic gait assessment; while Dao et al [27] use Microsoft's Kinect to gather data. Stowell et al [102] and Benson et al [10] each review prior research and highlight potential in medical use of wearables, including help for groups that disproportionately experience barriers to wellness. Eskofier et al [35] highlight the need for interdisciplinary collaborations when using wearable sensors in medical contexts; and McNaney et al [77] suggest opportunities for reflection on patient experience as one future use of sensing technologies in chronic neurological disorders such as Parkinson's disease. West et al [112] investigate the potential for wearables to change how medical data is gathered and used, highlighting the role of communication and analysis. Mentis et al. [78] suggests that sensors can be assistive in co-interpreting motor ability between patients and clinicians.

Wearable sensors are also used in remote patient monitoring, including for continuous assessment of hemiparetic stroke patients' recovery [49], epilepsy patients [101], for self-managing chronic health conditions [23], in gait assessment [5], mental health monitoring [31], and in early monitoring of COVID-19 patients [56]. Dobkin et al [32] suggest that wearable sensors enable clinicians to support rehabilitation when combined with telemedicine outreach. In rehabilitation contexts wearables might be used to gather data to develop precision interventions [66]. However, sensor data typically needs processing before it is usable, which may limit practicality and effectiveness [68]. In addition, because patients are unique it is important to focus on efficacy rather than performance when monitoring patient progress [62]. For example, Akinsiku et al [2] assess telerehabilitation systems for stroke survivors and argue for a reconceptualization in stroke telerehabilitation that is more inclusive of experimental information and patient accounts. Similar suggestions have been made for monitoring the general wellbeing of older adults [95]. Ryan et al [91] propose sensitive and flexible tracking tools to accommodate users patterns and purposes, in the context of attempting weight loss.

We build on this prior research by investigating how visualizations of biomechanical metrics, which are derived from data generated by MS patients longitudinal use of wearable sensors, might be best implemented to ease the adoption of new evidence-based clinical practices.

4 METHOD

In this section we first describe how our data were collected through one-on-one remote interview with clinicians. We then provide details about our qualitative analysis method. Finally, we describe in detail the low-fidelity prototype used as a design probe during our interviews.

4.1 Data Collection

This research was conducted under the approval of our university's Institutional Review Board (IRB-FY2021-5295). Data were collected

Table 2: Overview of study tasks

Themes	Example Tasks	Example Questions
Identify and describe the chart	1. Verbalize what each chart is displaying 2. Identify differences between different charts	*"What do you think is the difference between the featured chart in the center and the chart in the lower left?"*
Filter and change data attributes	1. Change date ranges 2. Change metrics displayed 3. Change gait assessment test locations	*"Can you show me how you would change this to a different date range?"*
Interpret and understand data items	1. Compare and contrast the charts presented 2. Interpret gait metrics 3. Identify normative population ranges 4. Key medical event identification	*"Based on how we displayed improvements and declines, are there any patterns that you see within this chart?"*
Describe the relationship to current practice and implications for future practice	1. Describe the impact on clinical work 2. Suggest improvements to increase clinical usefulness	*"How might having a visual comparison of a patient's current performance with past performance impact your work?"*

through remote video interview. We recruited a total of 10 experienced clinicians working in various roles in clinical neurology, physiotherapy and other rehabilitation practices associated with MS or similar neurological disorders, for participant details see Table 1. Participants were recruited through the extended networks of the project's members, and via our University's school of medicine. Each participant was interviewed individually online via Zoom by the first author. Interviews lasted between 30 minutes and 90 minutes (mean = 65 minutes), and participants received a $40 gift certificate as compensation. An informed consent was obtained, after which we probed participants on their professional background and on their current practice. We then described the aims of the research, provided a brief overview of the research into the potential role of data from wearable sensors in MS rehabilitation, and introduced the low-fidelity prototype.

Participants were each given a link to this Figma prototype, see 4.3, online so that they could interact with it directly. They were then asked to complete a set of tasks interacting with realistic synthetic data that we generated for the purposes of this study. These data were synthesized based on parameters reflecting a patient with mild to moderate gait impairment detailed by our clinical partners and with reference to prior research, e.g. [85] (Gait velocity: 1.10 +/- 0.22 m/s; Stride Length: 1.10 +/- 0.19 m; Step Length: 0.55 +/- 0.09 m; Contact phase: 64.4 +/- 3.99 %; Flight phase: 35.59+/-3.99 %; Cadence: 113.79 +/-15.61 steps/min; Stride Angle: 26.55 +/- 12.10 deg). The tasks participants undertook using the prototype were designed to act as a prompt to help us probe on opportunities and challenges that participants might identify with regards to incorporating visualized gait data that is collected remotely and longitudinally using wearables, into their practice. An overview of these tasks is shown in Table 2 and the full protocol is included in supplemental materials. While completing the tasks participants were asked to think-aloud, sharing thoughts on what they could see, what they felt about the way the information was presented, the degree to which it was clear, and how well they could understand what was in the interface. We also probed on how these visualized data might fit into their current practice and any opportunities they might see for new practices. Finally we gathered participants' impressions of the prototype's potential usefulness and usability in a clinical setting.

4.2 Analysis

Each interview was recorded using Zoom, and initial transcription was provided automatically. Two of the authors viewed each video individually multiple times, and amended the transcripts accordingly. Our analysis of these data was primarily guided by two sources, Seidman's guidelines for approaching interview data as qualitative research [96], and Braun and Clarke's approach to thematic analysis [17, 18, 73]. Unlike grounded theory approaches, which typically aim to articulate a unifying theory, these approaches draw connections across sources through threads. This process starts by researchers familiarizing themselves with the data by viewing and reviewing interview recordings, and reading and amending interview transcripts. Transcripts were then reorganized to bring together different participants' responses, based initially on codes adapted from [90]. Following this, key passages of interest were highlighted and additional codes applied, using an open coding scheme. This work was done using the MAXQDA 2020 software package. Code relation maps from the software provided cues for connections between different codes and participant responses, providing a starting point for the development of themes. Codes commonly used between participants and those strongly connected (often overlapping) with other codes were grouped together. Segments from participants' responses were grouped together using these code groups and then individually summarized. A side-by-side comparison of the segments and summaries revealed initial themes, which were then refined through a process of iterative interpretation and agreement reaching. Four researchers were involved in this process, which was led by the first author.

4.3 Gait Assessment Interface Prototype - The Design Probe

Our motivation in this study is to explore how state-of-the-art clinical research into longitudinal and remote gait assessment for MS and similar neurological conditions using wearable sensors might be translated into evidence-based clinical practice. To that end we

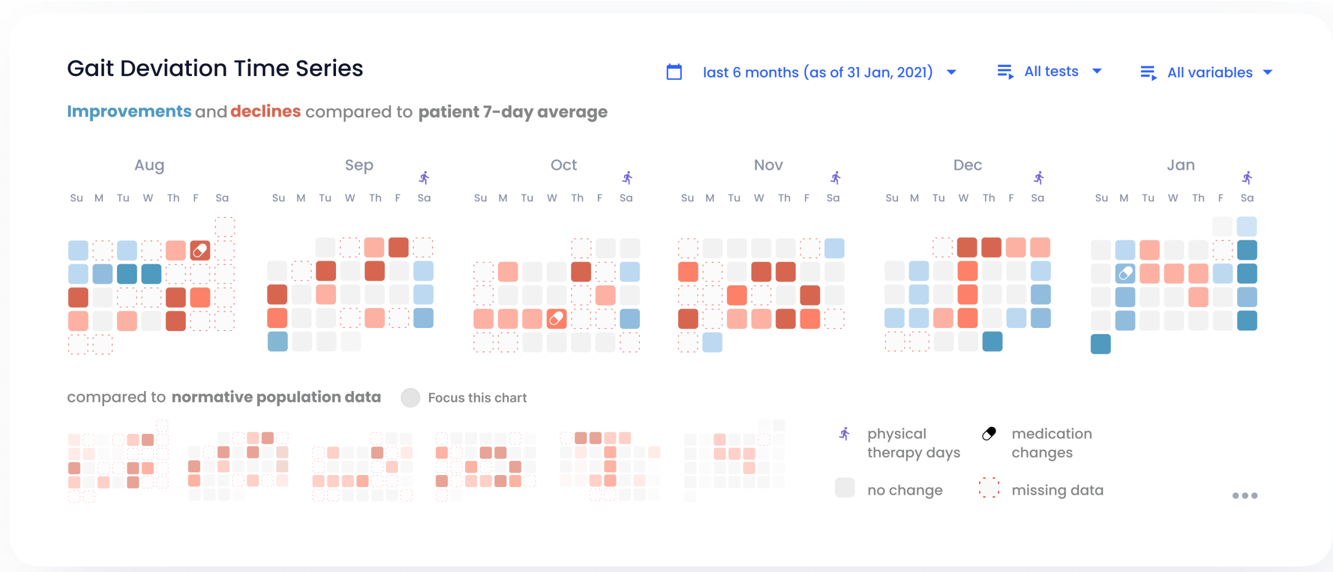


Figure 1: Gait Performance Time Series presented to participants

created a low-fidelity prototype using Figma, which we employed as a prompt to probe clinicians during interview. The prototype was co-designed by HCI, biomedical, neurology, and rehabilitation researchers, in an iterative process that highlighted the need for a deeper understanding of how clinicians might use sensor data and derived gait metrics to: (1) *access key information for clinical assessment*; (2) *make comparisons with baseline measures*; (3) *gain clinical insight from longitudinal and remote data*; and (4) *interpret progress indicators and key events*. The prototype's incorporated plots and features, and the interview protocol used to probe clinicians, were designed to spark conversation and prompt creative engagement around the possibilities offered by new evidence-based practices. We describe the prototype's interface in the section that follows, and provide a full reproduction in supplementary materials.

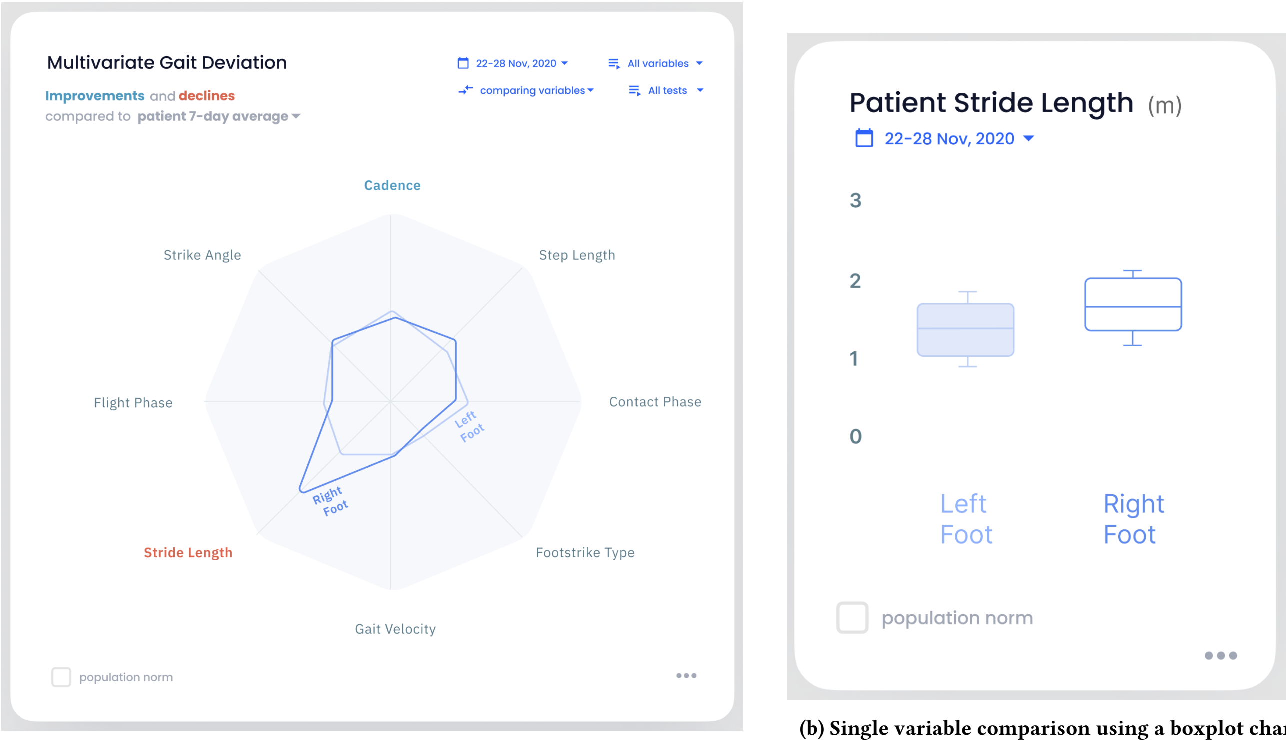
4.3.1 Gait Performance Time Series. The main screen of the interface is the "Explore" dashboard, which allows users to visualize the data from the shoe sensors. To give users an overview of recent data and inspire a search for patterns in the data, a heatmap (Figure 1) representing overall improvements and declines in a patient's gait compared to the patient's 7-day average was automatically displayed at the top of the page. The display shows these changes in performance using a divergent color scale where dark blue represents a higher level of improvements, dark red a higher level of declines in performance, and grey, the middle point represents no change. Missing data is represented by a box outlined in red dashes. The graph reflects data from a 6 month period for at-clinic and at-home collected data for several gait metrics outlined below. Users also have the option to filter these items as they wish, selecting a different time period, location of where data was collected, or set of gait parameters [21, 25, 30, 114].

- Gait Velocity: The mean velocity of progression (m/s)
- Stride Length: The longitudinal distance between two consecutive heel contacts of the same foot (m)
- Step Length: The distance between the point of initial contact of one foot and the point of initial contact of the opposite foot (m)
- Contact Phase: The duration of the phase during which the foot remained in contact with the ground (expressed as % gait of the cycle)
- Flight Phase: The duration of the phase during which the foot is not in contact with the ground (expressed as % gait of the cycle)
- Cadence: Rate at which a person walks (steps/min)
- Stride Angle: The angle of the parable tangent deriving from the movement of a stride (deg)

Physical therapy days and occurrences of medication changes are indicated on the graph using icons. While the main heatmap shows a patient's data compared their 7-day average, a secondary heatmap informs a clinician of how the patient is doing compared to the normative population.

4.3.2 Gait Parameter Comparison. To serve as an example of how our tool could be used to compare gait parameters the next visualization we display is a spider plot. In this plot each axis represents a variable. Both the left foot and right foot are represented by two different lines. The center point is represents the value 0. Categorical variables are converted to numeric ones. Population norm is displayed when toggled to provide clinicians with a reference (see Fig. 2a).

4.3.3 Single Variable Left / Right Foot Comparison. To serve as the last example of visualizations that could be created with the tool we presented a boxplot as another means to examine data at a more granular level. This plot allows users to see the different between the right and left foot and compare both values to the population norm (see Fig. 2b).



(a) Gait parameter comparison using a spider plot

(b) Single variable comparison using a boxplot chart

Figure 2: Screen designs from the prototype showing how a) multiple gait parameters are compared; and b) single variables are displayed

4.3.4 Insights. We included an 'insights' feature that presented trends that were found to the user to assist with their pattern recognition process. The example insight that is presented in the prototype is one where the system recognized that Fridays have more regression and Saturdays have more improvements.

5 FINDINGS

In this section, we present our analysis results, organized by the major themes identified. To set the scene, we first present a brief *background to current practice*, describing how clinicians structure their patient appointments and carry out gait assessments. Following this we present findings on how the detailed remote gait analysis that wearable sensors can facilitate might be introduced into clinicians' practices; and prompted by our prototype, how data might be visualized effectively to support clinicians' needs. Here we start with clinicians' *high-level objectives*, and then discuss *establishing goals* with patients. We also show that *understanding data in context* is important, and that support is needed for *collaborating with patients and colleagues*. Finally we see why clinicians might need to be *grasping critical information quickly*.

5.1 Background to current practice

To set some context for this inquiry, we first present a brief background to relevant clinical practices as described by participants. The typical duration of clinical appointments that participants described was 1 hour for an initial consultation and 30 minutes for follow-ups. However differences appeared when we discussed the frequency of appointments. For example, specialists may see medical patients anywhere from every three to six months, while physical therapists may see patients that need intensive rehab on a daily basis. During an initial consultation, the clinician will try to build a comprehensive picture of the patient's circumstances. For a neurologist this may involve understanding background information such as family history, conducting a neurological exam, and a review of labs and imaging. During follow-up appointments, clinicians focus on possible changes in how the patient is experiencing symptoms. This will typically involve discussing how the patient has been doing generally as well as talking about their disease and new symptoms or old symptoms. This will typically be followed by an exam and a review of medications. Gait assessments play a role in both initial and follow-up appointments. These are typically qualitative evaluations based on the clinician watching the patient walk normally and on uneven surfaces, and then pushing them (e.g. as if to catch a train) or undertaking particular exercises (e.g. a heel to toe walk or a tandem gait). Another aspect is to ask patients questions about their functional mobility and independence, as this is important in assessing quality of life. For example P10 told us, *"I don't ask specifically, 'Do you walk more?', but rather 'Did you go to the market?' or 'Did you meet a friend?'. Questions like this, easy* *questions but with the aim to understand if there is an improvement in the quality of life of the patient".*

5.2 High-level Objectives

While care is typically individualized, participants across clinical roles reported similar high-level objectives with regard to addressing mortality, morbidity, and morale by (1) focusing on patient safety and (2) maintaining community ambulation.

5.2.1 Focusing on Patient Safety. The clinicians' first objective in patient interaction is to establish and maintain a sense of patient safety, often with specific reference to the patient's risk of falling. This is because falls can be a sign of deterioration in the patient's condition or even a predictor for mortality. A patient's history of falls or risk of falling can also impact their care, in particular for those hospitalized as the risk of falls impacts whether they can be discharged or not. This is because a history of falls and fall risk places constraints on the types of treatments a patient can participate in, and because in the US the Centers for Medicare & Medicaid Services track falls as a key metric. It is also because it may reflect changes to a patient's perception of their own physical capacity. As P8 explained, *"They make improvements and they perceive that they can do more, they may put themselves in an unsafe position because they think they can walk further. They think they can walk without an assistive device".*

5.2.2 Maintaining Community Ambulation. The second high-level objective for clinicians is to increase or maintain community ambulation, which is the ability to move from place to place outdoors to support activities such as shopping, social outings; and leisure activities [72]. Here the aim is to increase independence and reduce the patient's need to spend lengthy periods of time in physical therapy. Understanding changes in gait metrics helps clinicians track progress towards the goals they agree with patients, and so clinicians are often trying to help patients increase their consistent gait speed as one aspect of independent community ambulation. P7 explained that this is because, *"The faster they walk the better they function, the more they're able to handle themselves in the community, and all those other parameters related to activities of daily living".*

5.3 Establishing Specific Goals

Establishing specific goals is an important aspect of the clinician-patient relationship. Clinicians discussed two distinct comparisons that would help in forming a baseline measure for goal setting, (1) comparing with normative data from healthy populations; and (2) the individual patient's current and potential abilities.

5.3.1 Comparing with Normative Data. Comparison of a patient's gait speed with normative data reflecting the typical speed of healthy populations helps clinicians and patients to set goals and targets. Clinicians are typically looking for patients to try to reach these normal average speeds as a measure of their capacity to perform activities of daily life. However, while comparison to normative data is important for clinicians, it is also important that the 'normal population' the patient is being compared to is appropriate with regard to demographics, medical condition, weight and height, etc.

5.3.2 Current and Potential Abilities. Not all participants shared the view that normative data are an important comparison. In particular, clinicians involved in physical therapy were more likely to suggest that understanding a patient's progress at an individual level should take priority. This was typified by P9 who said, *"Of course we want everyone to be normal. It's not going to happen. So what's the most important thing for that patient?".* These participants typically discussed being able to choose patient specific goals for progress tracking and ranking areas to work on by importance. Viewing our prototype, P3 suggested that it would be helpful to be able to input goals and see progress towards them.

5.4 Understanding Data in Context

Clinicians suggested a better understanding of gait analysis data could be gained if they were placed in context, by for example: (1) offering a better understanding of each patient's individual circumstances; (2) considering how the patient responds to treatment; (3) showing an everyday real-life picture; and (4) taking a longitudinal view.

5.4.1 Understanding Individual Circumstances. Clinicians suggested that having access to information that helps to contextualize a patient's experience would be useful in interpreting quantitative gait analysis data. For example, background information such as whether the patient lives alone, whether they work, and what their support network is like would help clinicians understand the challenges patients face. Beyond this, clinicians would want to know about the patient's functional status and whether they required an assistive device. Making this available within gait assessment interfaces is important to clinicians because of the high number of patients they typically see, and the challenges of relying on memory for these additional personal details. This was often about the underlying importance of personalizing treatments. P7 offered an example to explain this, *"If I have a patient with Parkinson's disease and they have worked out all morning doing rock steady boxing and then they come into me and they're exhausted, they're going to be performing differently than if I saw them first thing in the morning when they had their meds and things are stable".*

5.4.2 Considering Response to Treatment. Many factors contribute to clinicians assessing and assisting their patients, such as understanding the extent to which patients take their medications, checking MRI results or blood work, and even whether patients show up to appointments. A key aspect of this is understanding how patients are responding to changes in medication or physical therapy. In our prototype we had tried to account for some of this by including indicators for 'medication changes' and 'physical therapy days'. While these were considered useful as indicators, participants also suggested additional details like whether it was a change of dose or change in medicine. However, more detail is not necessarily more useful, and P6 suggested that the amount of medications a patient might need could make this problematic, *"Some people will have MS medications, blood pressure medications. Are you trying to collect all of those? I don't know if it's really helpful and maybe it is, but there may be a bit of an information overload and it may not be accurate for trying to capture all medication changes".*

5.4.3 Picturing Everyday Life. Clinicians also thought that contextual data around a patient's everyday life would be beneficial to understanding and interpreting longitudinal remote assessments. For example trying to better understand what is happening between visits, and if there are differences in how the patient is getting around at home as opposed to outside. This is because they were all very aware of the artificial nature of appointments in a clinical setting, and the differences experienced when a patient is more comfortable and less likely to feel they are being watched or tested. This view was exemplified by P2 who told us, *"One thing that I always wonder about when I see patients in the clinic is 'are they doing better or worse in the clinic than they are at home?'. We have white coat hypertension, and the nurses in our clinic tend to patients to start with and they do the timed 25 foot walk. And sometimes if it seems slow I'll have the patient go into a hallway and I'll walk with them and really encourage them and kind of push to go faster. They almost always come up faster when I do that, so it's interesting for me to know that they can do it"*.

5.4.4 Taking a Longitudinal View. Just as they believed information about changes in medication would support better understanding and interpreting the remotely generated data, clinicians also thought that the longitudinal remote data that sensors provide would help place a patient's progression and how to manage it in better context. This would allow them to continually track interventions and check that results from tests on day 1 are consistent with results from further into the program. Because conditions such as MS are chronic and require monitoring on an ongoing basis, our decision to show data from a six month period in our prototype prompted a number of participants consider longitudinal comparisons over a variety of periods in order to capture the subtle and slow changes that might otherwise go unnoticed. This may be even more important where a patient changes physician. A specific example of the particular benefits that longitudinal data may offer was provided by P2 who explained, *"It would be interesting to see if in the winter they walk a little faster and in the summer they walk a little bit slower. We could say, ' well, you should use a cooling vest if you want to walk faster'"*.

5.5 Collaborating with Patients and Colleagues

In this section we share participants' insights into the role that visualized gait analysis data might play in their discussions and collaborations with (1) their patients; and (2) their colleagues.

5.5.1 Collaboration with Patients. Because a clinician's perception of the way a patient is progressing does not always align with the patient's own view, it was common for participants to think of our prototype in terms of a platform to guide these discussions or motivate patients. Being able to discuss with a patient how they feel pre- and post-intervention, with reference to visualizations as a reminder, was one suggested example of how longitudinal data could be beneficial. This was seen as particularly beneficial where the patient may not be not experiencing incredibly dramatic robust improvements all the time. Similarly discussing the effects of new medication or simply sharing data to reassure patients that their gait metrics are within the expected range of the general population. P6 explained that, *"We talk a lot about exercise, we utilize walking as one of the main ways that they will exercise. They hear my spiel, and many of them will leave kind of motivated. But that motivation levels off, and then maybe they'll start again right before they see me again. It would be nice for them to paint a picture, see that pattern and feel that pattern. It would be nice to visually show them, and for me to have a way to track them"*. However this theme was typified when P1 told us, *"It's their body, and it's their life, so loop them into things rather than just doing the things without letting the other human being know"*.

5.5.2 Collaboration with Colleagues. Clinical work is typically undertaken as part of a team. Several participants referenced team work as important to treating patients, and noted that different team members might have different needs and interact with gait metrics differently. For example, while neurologists might not typically directly assess gait, it is likely they would want to view a patient's progress. Participants also discussed using our prototype, in particular the 'insight' tool, as a possible platform for collaborative decision making, e.g. with referring physicians. P1 described their current collaboration in more detail, *"I do all outpatient work, and the way our clinic is set up, we have this amazing multi-disciplinary team. We have nurses, nurse practitioners, neurologists, we have neuropsychiatrists. We have an entire research team. I don't work alone. I work with this amazing team, and so what I do is have my schedule, patients are booked for 30-minute follow-ups, and I collaborate with my colleagues. Sometimes I'm seeing patients that I just follow more independently, and then sometimes, I'm seeing patients for the first time; maybe they're seeing one of my neurologist colleagues more regularly, and then they're coming in to see me for an urgent visit"*.

5.6 Grasping Critical Information Quickly

Clinical situations are often fast-paced and high-pressure. As a consequence it was typical for participants to highlight that their work is time critical. However they also need all the available information to make informed decisions. This can lead to a potential tension between (1) having direct access to important information; and (2) exploring data in more detail.

5.6.1 Direct Access to Important Information. We found that clinicians often say they want access to data they can quickly grasp, indicating that they have very little time to prepare for patient visits. In this context it was considered important that data were ready to be acted on and wouldn't slow down clinical activities in the short time available for patient visits. Here clinicians typically spoke in terms of efficiency, simplicity, speed, and accuracy, potentially provided in a composite score that would effectively summarize a patient's gait. This perspective was typified by P3, *"We know in gait studies that stride length and things that correlate with falls and ability to ambulate in the community, that's what the data supports, then that would be my dashboard to highlight those key things. Then if you want to drill down with it, to know all these other parameters about flight and contact and strike that would be nice to know. But what I want smacking people in the face is what are really the key performance metrics"*.

5.6.2 Exploring in More Detail. While it was typical for clinicians to highlight the value of concise and critical information, there were also circumstances in which they would want to be able to delve deeper and in more detail. For example to consider different types of gait pattern, such as comparing the different phases for each side of the body. Another reason for wanting the ability to take a deep dive into the data would be to offer increased patient value as represented by specific detailed analysis and metrics that would enable clinicians to characterize a particular patient's patterns of relapse. This was explained in detaile by P6, *"MS has different forms, we have relapsing remitting MS where patients have relapses and they get better. One thing to do is to characterize what patients look like during their relapses. The other thing that I think is more important, is when they transition from relapsing remitting to secondary progressive, where they stop having attacks but they just slowly get worse and we have no really good way to say, 'Okay, well, this is the time that this is happening'. We can't quantify the time that is happening, and so we're going to only do it retrospectively. So if we see an ongoing decline in their ambulation, this may be a really nice way to figure that out and to characterize and present this data to the patient"*.

6 DISCUSSION

In this section we discuss our findings in light of prior research and introduce the design recommendations we identified. Discussion is focused around 4 themes: 1) *reflecting patient narratives*; 2) *responding to clinicians' priorities*; 3) *partnering with patients*; and 4) *anticipating changing circumstances*.

6.1 Reflecting patient narratives

Initially referring to the stories patients shared about their own experiences [51], patient narratives have now become a familiar feature of patient-centered care [13]. In clinical practice they offer supportive tools for conveying causality [46], and facilitate continuity and transfer of care between clinical teams [108]. Our findings suggest that clinicians would likely use this framework to make sense of quantitative gait metrics. For example, clinicians discussed connecting remote gait assessments to key events, relationships, and environmental changes, to help determine risk and suggest potential treatments. We see this when P2 discusses addressing mobility difficulties using a cooling vest (5.4.4). Similarly, our findings on community ambulation (5.2.2) reflect prior research [5] in suggesting that in-clinic gait assessments fail to capture the way in which mobility changes with circumstance and setting. Longitudinal data that better capture a patient's experiences with hilly streets and busy or uneven sidewalks offer a more complete story of gait and mobility trends in various contexts, and support the collaborative reflection participants suggested (5.5.1). Care is needed to avoid reinventing the wheel by mirroring existing electronic health records (EHR) or increasing complexity, as participants were concerned about information overload (5.5.1), but guidance can be found in literature discussing problem-centric visualizations [20] or medical data modeling [53]. Enabling clinicians to compare data collected in different contexts would add richness to patient narratives. For example, comparing data before and after a medical intervention; comparing between different medications or physical therapy exercises; or comparing data collected during the morning or during evening. With the addition of weather report data, comparison might also be made between days when it is hot vs cold or humid vs dry to offer insights on gait adaptations in inclement weather. Such detail could also support cross-care insights. This has been shown to improve communication between nurses, e.g. during shift changes, and reduce the likelihood of a life-threatening clinical event going unnoticed or misinterpreted [42]. While there are opportunities for future HCI research to investigate how AI could mine electronic health records and clinical notes to support clinical event detection and make patient outcome predictions, designers should initially support easy access to information and avoid data mirroring or deep integration with existing complex medical systems.

6.1.1 Design recommendations.

(1) **Integrate Patient Demographic and Mobility Information.** While avoiding replicating existing healthcare records, selected patient details should be included within systems for remote and longitudinal rehabilitation assessment. For example, the patient's age, height, and weight, and whether they use an assistive device when walking. Information about comorbidities or prior surgery should be easily accessible.
(2) **Indicate Where Data Were Generated.** Where possible show whether data were gathered in a clinical setting, at the patient's home, or in other locations, and characterize activities that were taking place. Indicate this in place with the data, e.g. through iconography or color coding, and provide a filter for users to change which data are displayed.
(3) **Support Connection to Health Records Data** To integrate sensor data from remote and longitudinal gait assessments into clinicians' existing work practices provide cross referencing indexes to existing electronic health records, e.g. using URL shorteners and trackers in a similar way to bit.ly. Also allow clinicians to connect to relevant public information, such as weather data, to recreate particular information ecologies. These cross referencing indexes might utilize APIs and create stored queries.
(4) **Visualize Key Clinical Events**. Enable clinicians to quickly visualize key events that may be recorded in other systems, such as changes to medication, modifications to physical therapy treatments, or hospitalizations. Build on the cross referencing indexes discussed above and provide a simple graphical language and filters that change the visualization.

6.2 Responding to clinicians' priorities

Clinicians often perceive themselves to be under considerable time constraints and pressure [67]. Because of this participants, who must cover additional ground beyond gait assessments, valued quick access to important information. While wearable sensors offer fine-grained gait parameters that support improved evidence-based practices, for this information to be meaningful designers should link it to familiar concepts, and clinical objectives and treatment options. Providing visual cues for quick access to relevant insights will help clinicians adopt new practices and therefore support the in-depth exploration discussed by P9 and P6 in particular. This might be implemented through a 'gait index score' composed of several parameters, with the capacity to view and change how parameters are weighted in order to help clinicians interpret results; an approach used similarly by Hirsch et al. [52]. Prior literature also offers guidance in connecting data points to familiar concepts [9, 22, 53, 105], summarizations [37], and supportive text-based information [104], which is important when cognitive load reduces use of clinical data [65, 113]. Moving beyond clinicians' time constraints, it is important to support assessments of progress towards patient goals, because setting and achieving shared goals is an important aspect of care. Centering data representations around these actionable objectives is another way to provide clinicians with the information they need efficiently and effectively. This might be achieved through trend lines or stepping stones in goal metrics.

6.2.1 Design recommendation.

(1) **Visually Connect Clinical Objectives and Patient-Specific Goals With Gait Parameters.** Provide appropriately placed indicators to support quick access to derived measures that connect gait metrics to clinical objectives, such as community ambulation and fall risk. Similarly provide indicators that show progress towards individualized goal attainment and highlight key assessment metrics, e.g. trends towards population norms or towards particular individualized targets. This provides the clinician with quick access to actionable information and a stepping stone towards more in-depth investigation of objectives such as improving balance or endurance.

6.3 Partnering with patients

Our findings highlight how important mutually agreed goals, shared reflection, and conversation are to clinicians' relationships with their patients, and that participants would share visualized data with patients as a means of encouragement. For example, demonstrating improvement through data might initiate a positive feedback loop and inspire patients to continued progress. This was because progress can be too small for the patient to experience strongly in their everyday activities, yet significant enough to be clearly apparent when visualized. Prior research is divided over how best to achieve this. For example, Chen et al. [22] suggest data from gait sensors should be visualized in ways that reflect gait cycle, i.e. toe-off, flight phase, heel-strike, foot-flat, in order to help non-experts' interpretation; while Wu and Munteanu suggest that patients prefer numerical to graphical indicators of actionable high-risk metrics, such as fall risk [116]. Future HCI research should identify specific ways of visualizing gait sensor data that are meaningful to both clinicians and patients to support their shared interactions.

6.3.1 Design recommendation.

(1) **Visualize Data to Support Patient-Clinician Interactions**. Carefully consider visualization choices to support clinicians conversations with their patients. While using charts likely to be familiar to a broad audience can help, it remains important to include visual cues indicating how the chart should be read.

6.4 Anticipating changing circumstances

Our findings also suggest that clinicians value the potential for longitudinal remote assessment data to help predict outcomes and suggest interventions, based on statistical analysis or using machine learning models. This aligns with prior research, e.g. [23] linking perceptions of the value of wearable sensor data to how clearly they are connected to treatments and outcomes, and to predicting recovery [49, 60, 66]. Future HCI research in this area might build on work such as [37], and investigate how predictions based on data from wearable sensors might be visualized to provide useful information for clinicians.

6.4.1 Design recommendations.

(1) **Provide Visual Indicators to Track Trends.** Offer visual cues to highlight trends in data that will support clinicians in assessing the causes of changing gait. For example, by adding reference lines, milestones, and projections. At the same time remain sensitive to nuanced changes over shorter periods that may also have important clinical implications.
(2) **Offer Machine Predictions Transparently.** Incorporate machine learning or other automated statistical predictions transparently by providing access to how they were generated. For example, indicate which parameters were involved and how they were weighted. Also support clinicians in interpreting and interrogating predictions, and prompt them to consider patient-specific contexts that suggest predicitions should be contested.

6.5 Limitations

There are 3 main limitations to this study that should be acknowledged. First, as an exploratory study, the work reported here involved engaging with a limited number of MS rehabilitation practitioners, and its primary focus was at a single medical center. This can have significant implications in terms of the study's generalizability. Hospitals and care sites differ in the technology available to healthcare workers, and future HCI research should take care to contextualize design within the environment in which the technology is likely to be used. Consideration should also be taken for participants knowledge and experience with wearable sensors, a question we did not ask. The generalizability of findings could be further enhanced through studies of other clinical practitioners with different roles in the rehabilitation and treatment of MS and similar neurological diseases. Second, while this study focused on MS rehabilitation practitioners, the research would benefit from the perspective of MS patients. In particular, although the prototype used in the study was designed for practitioners' current practice, which like many healthcare technologies may not involve direct data-centered interaction with the patient, its potential as an aid for patient-provider communication was highlighted by some participants and would benefit from future research. A third limitation of the study concerns systems integration and workflow alignment. For a prototype such as the one described in this paper to be incorporated effectively and productively into the workflows of MS practitioners, further research and investment is needed to study its integration within or alongside the EHR system used at the care site; as this may introduce additional constraints or considerations with regard to its usability and usefulness.

6.6 Future Design Work

Future work for our research includes designing and evaluating further iterations of the visualization interface, based on the initial guidelines presented here. This starts with making enhanced visual connections between specific clinical objectives and particular gait parameters being considered during longitudinal assessments. For example, we might use a series of slope charts to represent the difference between two selected time points, e.g. "Before" and "After", for each gait parameter. In this way we might summarize how that specific gait parameter has changed, and show whether the change is significant. Further information might be provided that lists the interventions that have taken place during the time period selected, enabling the clinician to select an intervention as the basis for the before and after comparison. As we move forward with this future work we will need to evaluate how each iteration might impact clinical understanding and decision-making, e.g. with regards to assessing the effectiveness of interventions. Future work within this ongoing design research is also being planned with regards to investigating how data driven insights might be categorized according to clinical objectives, such as fall risks, community ambulation, and intervention assessments. We might feature insights derived from particular patterns of change in the data as it relates to these objectives in prominent places, such as the top of the page, along with active interventions and related gait metrics or outcomes. Here we must evaluate how this information might impact clinicians' decision-making confidence, or investigate the degree to which contextual information is necessary for understanding insights potentially offered by data from wearable sensors.

7 CONCLUSION

In this paper we present our inquiry into the design requirements for data-rich interfaces that visualize detailed biomechanical gait metrics for clinicians treating patients with MS and similar neurological conditions. Using a prototype interface that was co-designed by HCI, biomedical, neurology and rehabilitation researchers as a design probe, we interviewed 10 experienced clinicians from a range of rehabilitation roles. Our findings help to characterize challenges associated with introducing data-focused technologies into healthcare settings, and suggest ways to support their role in developing new evidence-based practices that offer benefits to clinicians and their patients. Based on these findings we offer a set of design recommendations for visualizing the detailed biomechanical metrics that can be derived from wearable sensor data, which are centered around supporting clinician needs and easing the transition between clinical research and clinical practice. Understanding and responding to the challenges of designing interfaces that can support this transition through effective visualization of data and metrics that support clinicians' insight, has implications for HCI research across healthcare and related domains.

ACKNOWLEDGMENTS

We would like to thank all of the clinicians that participated in this study. We gratefully acknowledge support from the National Science Foundation (Awards 2129076; 1928614).

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