ANNALS of Clinical and Translational Neurology
Open Access
AMERICAN NEUROLOGICAL ASSOCIATION

RESEARCH ARTICLE

"Self-care selfies": Patient-uploaded videos capture meaningful changes in dexterity over 6 months

Arpita Gopal[1], Wilson O. Torres[2], Ilana Winawer[3], Shane Poole[1], Ayushi Balan[1], Hannah S. Stuart[2], Nora E. Fritz[4], Jeffrey M. Gelfand[1], Diane D. Allen[3] & Riley Bove[1]

[1]Department of Neurology, University of California, San Francisco, California, USA
[2]Department of Mechanical Engineering, University of California, Berkeley, California, USA
[3]Department of Physical Therapy and Rehabilitation Sciences, University of California, San Francisco, California, USA
[4]Department of Neurology and Program of Physical Therapy, Wayne State University, Detroit, Michigan, USA

Correspondence
Riley Bove, Department of Neurology, University of California, San Francisco, CA, USA. Tel: 1 415 353 2069;
E-mail: riley.bove@ucsf.edu

Received: 25 July 2023; Revised: 3 October 2023; Accepted: 4 October 2023

Annals of Clinical and Translational Neurology **2023; 10(12): 2394–2406**

doi: 10.1002/acn3.51928

Abstract

Objective: Upper extremity function reflects disease progression in multiple sclerosis (MS). This study evaluated the feasibility, validity, and sensitivity to change of remote dexterity assessments applying human pose estimation to patient-uploaded videos. **Methods:** A discovery cohort of 50 adults with MS recorded "selfie" videos of self-care tasks at home: buttoning, brushing teeth, and eating. Kinematic data were extracted using MediaPipe Hand pose estimation software. Clinical comparison tests were grip and pinch strength, 9 hole peg test (9HPT), and vibration, and patient-reported dexterity assessments (ABILHAND). Feasibility and acceptability were evaluated (Health-ITUES framework). A validation cohort ($N = 35$) completed 9HPT and videos. **Results**: The modality was feasible: 88% of the 50 enrolled participants uploaded ≥3 videos, and 74% completed the study. It was also usable: assessments easy to access (95%), platform easy to use (97%), and tasks representative of daily activities (86%). The buttoning task revealed four metrics with strong correlations with 9HPT (nondominant: $r = 0.60$–0.69, dominant: $r = 0.51$–0.57, $P < 0.05$) and ABILHAND ($r = -0.48$, $P = 0.05$). Retest validity at 1 week was stable ($r > 0.8$). Cross-sectional correlations between video metrics and 9HPT were similar at 6 months, and in the validation cohort (nondominant: $r = 0.46$, dominant: $r = 0.45$, $P < 0.05$). Over 6 months, pinch strength (5.8–5.0 kg/cm^2, $P = 0.05$) and self-reported pinch (ABILHAND) decreased marginally. While only 15% of participants worsened by 20% on 9HPT, 70% worsened in key buttoning video metrics. **Interpretation**: Patient-uploaded videos represent a novel, patient-centered modality for capturing dexterity that appears valid and sensitive to change, enhancing its potential to be disseminated for neurological disease monitoring and treatment.

Introduction

The hand is the most active part of the upper extremity, and hand function is critical to independence in activities of daily living (ADLs).[1] Neurological conditions can result in worsening in hand function, whether acutely (stroke) or more gradually (multiple sclerosis (MS) or Parkinson's disease). Changes in function and manual dexterity can affect quality and independence of performance in daily tasks, ability to perform at work and remain employed, and engagement in recreational activities.[2,3] Assessments sensitive to changes in hand function could inform disease progression, or response to pharmacological[4] and rehabilitation strategies. To this end, remote assessments have been explored; existing options—smartphone-based applications,[5,6] wrist-worn accelerometers,[7,8] and specialized keyboards,[9,10] allow quantification of activities of daily living in naturalistic environments. While innovative, these technologies pose challenges in implementation and scalability. Alternatively, wearable devices for hand gesture recognition, including gloves with embedded inertial measurement units (IMUs) or flexible sensors are relatively low-cost and simple to produce.[11] However, there are limitations to the number of sensors in each glove, and the associated equipment (e.g., processing unit) hinders its use in a patient's naturalistic environment.[11]

Prioritizing the needs and preferences of patients, patient-uploaded videos represent an entirely different approach to the remote monitoring of dexterity. They leverage accessibility ("bring your own device", i.e., use of preferred devices and software), usability (video "selfies": a convenient, modern communication medium), and meaningfulness (capturing self-care tasks critical to independent living). To analyze these videos, pose estimation: a set of algorithms capable of detecting body landmarks and their movement in space, is gaining acceptance in healthy populations (e.g., in the lower extremity to quantify features of gait[12,13]). To date, however, pose estimation has mostly been validated as a method for capturing precise data on movement in healthy human populations, and not to our knowledge as a clinical evaluation in MS or other neurological populations.

The current study sought to validate patient-uploaded "self-care selfies" as a method of remotely monitoring dexterity data for a neurological population. Specific aims were to (1) evaluate the feasibility of video collection at single and longitudinal timepoints, (2) validate dexterity measures extracted from videos using a proof-of-concept, open-source pose estimation algorithm, and (3) evaluate whether subtle worsening in hand function over 6 months could be captured in videos. The overarching goal is to provide a granular, clinically meaningful metric of movement in the natural environment that can be used to measure progression and/or improvement in clinical trials and to inform clinical care and neurological rehabilitation.

Methods

Study setting and participants

Discovery cohort. A convenience sample of 50 adult patients with a confirmed diagnosis of MS (by 2017 McDonald Criteria) were referred by their primary neurologist at the University of California, San Francisco (UCSF) Multiple Sclerosis Center to the study team. All referred participants met the additional eligibility criteria (smartphone ownership, smartphone literacy test).

Study procedures

At baseline and 6 months, in-clinic assessments of hand function were grip and pinch strength (Jamar Technologies dynanometer),[14] quantitative vibration sense (Vibratron II- Physitemp),[15] and the 9HPT (standard for assessing dexterity in MS).[16] The Action Research Arm Test (ARAT) was also included as a comparsion for in-clinic assessment, but it was not included in analysis as the cohort reached a ceiling effect. Participants were then trained (for approximately 5 minutes) to use the institutionally approved Research Electronic Data Capture (REDCap) platform[17] to complete the remote patient-reported outcome (PRO), ABILHAND (23 items summarized in pinch and grip subscores),[18] and to upload their videos. Participants were asked to position the smartphone an arm's length away in portrait orientation using the front-facing camera. These instructions were included in REDCap for reference when uploading videos at home. Participants were sent an invitation to complete these remote assessments (PROs plus video upload) via email weekly for months 1–3 and monthly for months 4–6. Assessment frequency was intended to identify if practice effects occurred from repeated, early trials,[19] while reducing overall participant burden. Participants had 48 h to complete each assessment, to ensure reasonably regular intervals between weekly assessments. Participants received one reminder email 24 h after the initial email was sent.

Videos and PRO results were stored securely in institutionally approved, firewall- and password-protected platforms, REDCap and Box. Videos were uploaded directly through REDCap rather than saved to participants' personal devices to mitigate data loss and ensure privacy.

Video tasks

Participants self-recorded videos of performance of three basic ADLs that require hand function[20]: dressing (buttoning a shirt), personal hygiene (brushing teeth), and feeding (fork to mouth). Example videos were provided within REDCap. Feeding and personal hygiene tasks were uploaded once per hand, for a total of five videos per timepoint.

Study feasibility and acceptability

This was evaluated via monthly REDCap survey using the validated Health Information Technology Usability Evaluation Scale (ITUES)[21] framework, which evaluates usability to ultimately inform the ease of adoption of new technologies.

Validation cohort (cross-sectional)

To ensure that the key cross-sectional findings were stable, a second sample of 35 patients meeting the same eligibility criteria was enrolled to provide the following information: baseline demographic and clinical measures, 9HPT, and self-care videos.

Ethical approvals

All study activities were approved by the UCSF IRB (IRB# 20-557) and all participants provided written informed consent.

Video analysis

Pose estimation has been tested and successfully validated in healthy populations. "To estimate 3D hand pose from 2D patient-uploaded videos, MediaPipe Hand from the OpenCV library was selected. A freely available machine learning solution, MediaPipe is a high-fidelity finger-tracking solution that has been validated for clinical applications[22] against RGB 3D-motion capture cameras[22] and detects 21 landmarks in the hand, including the wrist."

Based on the variable grips required for each of the ADLs, the tip of the index finger and wrist landmarks were chosen for analysis (Fig. 1). For each landmark, position and velocity kinematic data were obtained by mapping the joints of interest onto the real-world xy-cartesian coordinate system using MediaPipe's technology (Fig. 1). The following metrics were generated: (1) path length of the landmark, a measure of the joint movement in the cartesian plane; (2) complexity of movement, a count of the number of local peaks in the position vs time curve; (3) total distance the joint travels, the area under the velocity versus time curve (AUC); and (4) smoothness, average velocity divided by maximum velocity (Table S1).

A video was considered valid if ≥10 coordinates were generated during analysis. Sampling frequency was established based on the frame rate of the uploaded video. Before extracting metrics from each task, videos were not preprocessed, but were manually reviewed to remove extraneous activities recorded (e.g., adjusting the camera before beginning activity). Participants used their own devices, which resulted in differences in video frame rate.

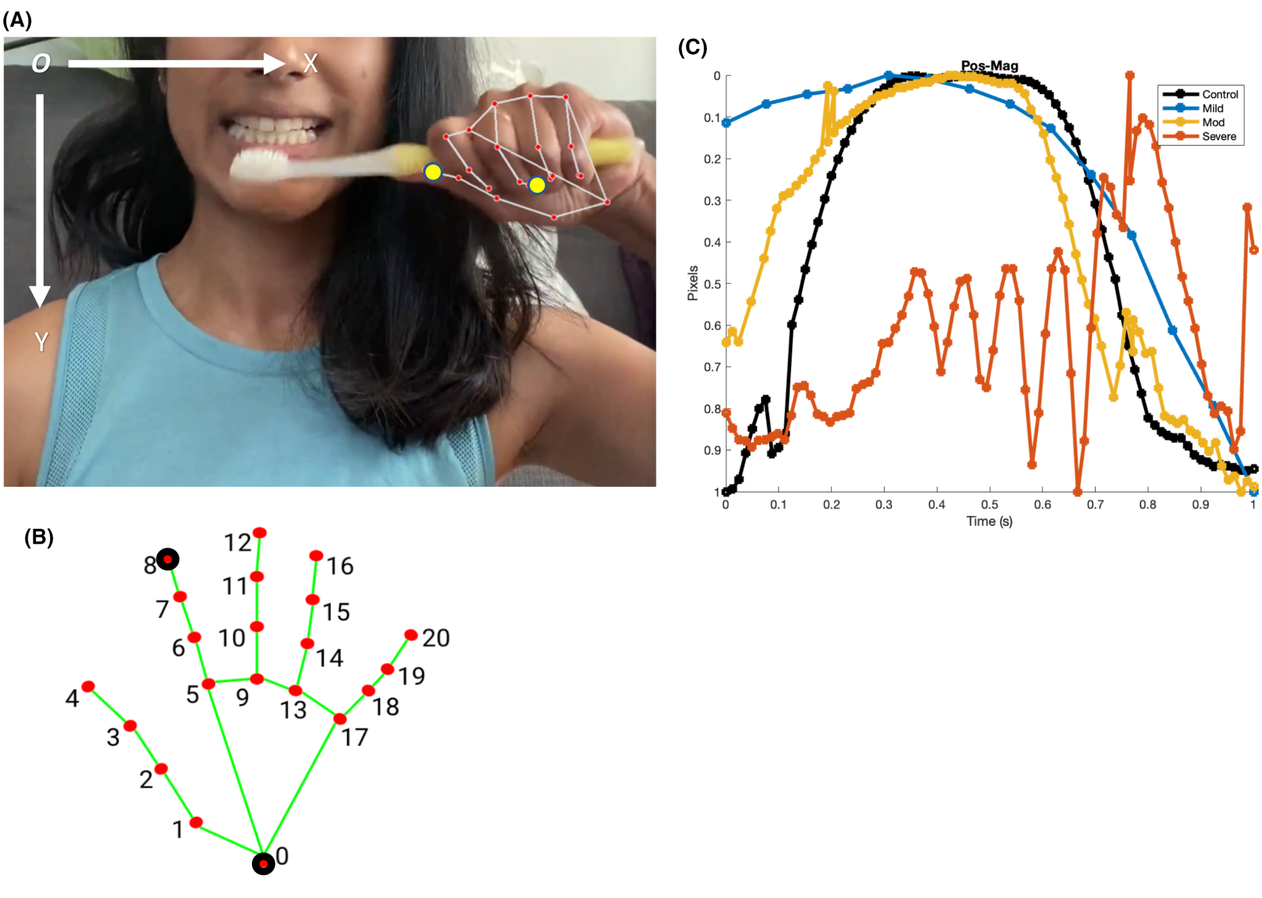

Figure 1. Pose estimation landmarks for video analysis. (A) Depiction of skeleton overlay in MediaPipe Hand. Index finger and wrist landmarks are highlighted in yellow. Coordinate system for video kinematics, with O at the origin. (B) All available landmarks in MediaPipe Hand. Point 8 represents the index finger and Point 0 represents the wrist. (C) Path length trajectory for index finger in eating task over 1 sec. Each participant is depicted by a different colored line (black: control; blue: participant with mild MS (EDSS 0–2.5); yellow: participant with moderate MS (EDSS 3–5.5); red: person with severe MS (EDSS > 6). The *Y* axis depicts the distance traveled by the landmark in pixels relative to the origin (A).

To standardize, we used the video duration to estimate instantaneous frame rate, which was then averaged over the length of the video.

An initial script was developed to analyze videos using MediaPipe; this is now optimized to automatically generate data on one video per minute and available on GitHub (https://github.com/UCSF-MSLAB/self_care_selfies).

Statistical analyses

To describe the study population, feasibility, and correlates of adherence, descriptive statistics and unpaired *t*-tests were used. To determine the associations between demographic data, video kinematics, PROs, and clinical dexterity measures, Spearman's correlation coefficients were calculated. To quantify statistically significant changes in each clinical and video measure over the study period, paired *t*-tests were conducted. Given the large number of variables available through MediaPipe, it was *a priori* decided that the task with the strongest cross-sectional correlations ($r > 0.60$) with 9HPT would be selected for longitudinal analyses. Spearman's correlation coefficients were calculated to determine correlations between clinical and video metrics at both 0 and 6 months. Video analyses were performed using Python 3.4; kinematic and statistical analyses, and data visualizations were performed in Matlab 2022.

Results

Participant demographic and clinical characteristics

Among the 50 enrolled Discovery cohort participants, 62% were women and 73% non-Hispanic White; mean age was 47.2 years (SD: 12.9), and median patient-reported EDSS[23] disability was 3 (IQR: 2–5) (Table 1). Based on a 9HPT cut-off of 33.3 sec, 90% of participants had high and 10% had low dexterity.[24] In-clinic dexterity measures showed some associations with demographic (older age, female sex) and clinical (MS duration) features (Figure S1). The Validation cohort did not differ in any key features ($P > 0.05$ for each comparison, Table S2).

Feasibility of longitudinal patient video uploads

Engagement

After enrollment, 44 out of 50 (88%) Discovery cohort participants provided at least 1 time point of video uploads, 2 withdrew from study due to relapses, and 4 were lost to follow-up.

Table 1. Discovery cohort demographics and baseline characteristics.

Gender, *N* (%)	
Men	18 (36%)
Women	31 (62%)
Nonbinary	1 (2%)
Age, mean (SD)	47.2 (12.9)
Race, *N* (%)	
White, non-Hispanic	44 (73%)
Black	1 (2%)
Asian	4 (8%)
Hispanic	1 (2%)
Baseline EDSS, median (IQR)	3 (2, 5)
Disease duration (years), mean (SD)	14.3 (9.2)
MS subtype, *N* (%)	
Relapsing remitting	43 (86%)
Primary progressive	4 (8%)
Secondary progressive	3 (6%)
Dominant hand, *N* (%)	
Right	45 (90%)
Left	5 (10%)
Smartphone type, *N* (%)	
iOS	40 (80%)
Android	10 (20%)
Grip strength (kg/cm^2), mean (SD)	
Dominant	28.6 (9.4)
Nondominant	27 (9.5)
Pinch strength (kg/cm^2), mean (SD)	
Dominant	5.8 (2.6)
Nondominant	5.6 (2.5)
Nine-hole peg test (sec), mean (SD)	
Dominant	23.5 (9.7)
Nondominant	28.7 (14.9)
Vibration sense (Hz), mean (SD)	
Dominant	2.4 (2.7)
Nondominant	2.3 (2.6)
ABILHAND, mean (SD)	
Pinch subscore	29.5 (4.6)
Grip subscore	35.5 (4.4)

Study adherence

For the 37 6-month study completers, 345 total videos were uploaded at the baseline and 6-month timepoints; 12 could not be analyzed, and kinematic metrics could not be extracted from 54, leaving 279 (80.9%) videos to be analyzed. No participants providing remote data experienced relapses. The 44 remotely engaged participants, and the 37 study completers, did not differ from the entire ($N = 50$) cohort in terms of age, sex, race/ethnicity, disease duration, or baseline 9HPT ($P > 0.05$ for each variable compared; Fig. 2).

Acceptability

The study assessments and overall design were well-received by most participants both in their qualitative and quantitative responses (detailed in Table S3).

Usability

A majority strongly (77%) or somewhat (18%) agreed that the assessments were easy to access, and a majority strongly (61%) or somewhat (36%) agreed that the remote uploading platform was easy to use, "without technical issues." None disagreed with these statements.

Relevance

Most participants strongly (43%) or somewhat (43%) agreed that the tasks performed in the videos were representative of their daily activities. Qualitatively, buttoning was noted as being "more challenging than I remember."

Video quality

Mean video duration was 12.1 sec (SD: 5.6, median: 7.2 sec, range: 3–165 sec). Of 250 total baseline videos (N = 50, 5 tasks each), 16 (6.4%) were not analyzed due to low video quality or participant error (e.g., participant forgot to press record); of the 234 others, 36 (15.4%) did not generate sufficient data by MediaPipe Hand for kinematic analysis (generating fewer than 10 coordinates per video). This left 198 (79%) videos, from 95% participants, to be analyzed. Low (>33.5 sec)[16] 9HPT scores were not associated with difficulty using the survey platform or completing video uploads (Pearson's correlation, $P > 0.05$).

Cross-sectional validation of video metrics

Validation against clinical measures

Discovery cohort (N = 50)

The buttoning task yielded measures with the strongest correlations with standard in-clinic assessments of hand function (Figs. 3–5). In the nondominant hand, 9HPT was strongly correlated with wrist position path length ($r = 0.66$, $P = 0.011$), wrist position peaks ($r = 0.65$, $P = 0.010$), index position path length ($r = 0.69$, $P = 0.012$, and index position peaks ($r = 0.68$, $P = 0.009$). Further, vibration sense was also correlated with wrist position path length ($r = 0.39$, $P = 0.045$), index position path length ($r = 0.46$, $P = 0.006$), and wrist position peaks ($r = 0.35$, $P = 0.019$). In the dominant hand, these correlations between buttoning metrics and 9HPT ranged $r = 0.51$–0.57, $P = 0.03$–0.05. More modest correlations were found for the brushing and eating tasks (Table S5).

To ensure that these associations were stable across different time points, cross-sectional correlations at 6 months were also analyzed. Similarly, the buttoning task demonstrated the strongest correlations between 9HPT in the nondominant hand (wrist position path length ($r = 0.71$,

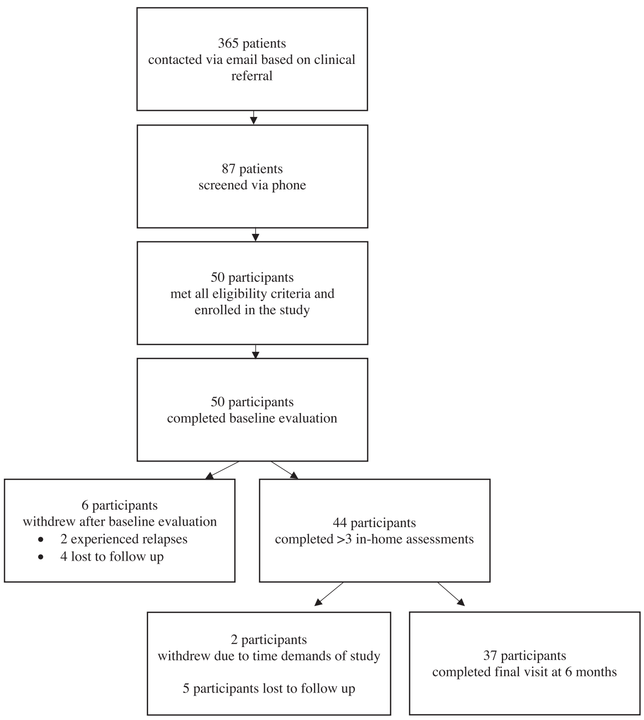

Figure 2. Participant recruitment and retention diagram, tracking patient contacts, enrollments, withdrawals, and completion.

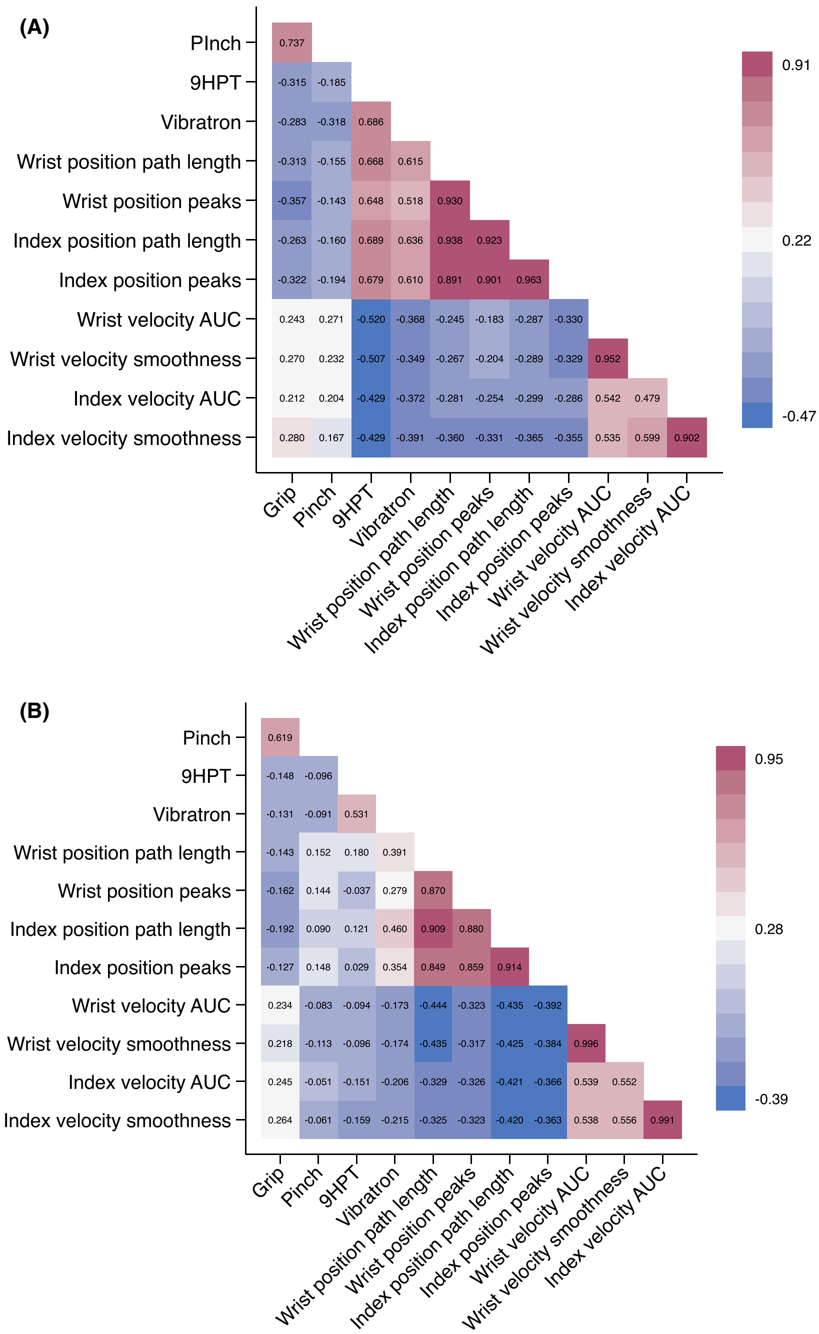

Figure 3. Spearman's correlation coefficients heatmap, buttoning task. Darker pink colors indicate *r* values closer to 1, and darker blue colors indicate values closer to −1. (A) Buttoning dominant hand (B) buttoning nondominant hand.

$P = 0.012$), wrist position peaks ($r = 0.59$, $P = 0.023$), index position path length ($r = 0.61$, $P = 0.019$), and index position peaks ($r = 0.52$, $P = 0.031$).

Validation cohort ($N = 35$)

The validation cohort did not differ from the Discovery cohort in any key clinical or demographic features (Table S2). Mean 9HPT for the dominant hand was 25.3 sec and for the nondominant hand was 26.9 sec. Again, as for the Discovery cohort, the buttoning task yielded measures with the strongest correlations with 9HPT scores. In the nondominant hand, 9HPT was correlated with wrist position path length ($r = 0.45$, $P = 0.021$) and wrist position peaks ($r = 0.42$, $P = 0.010$).

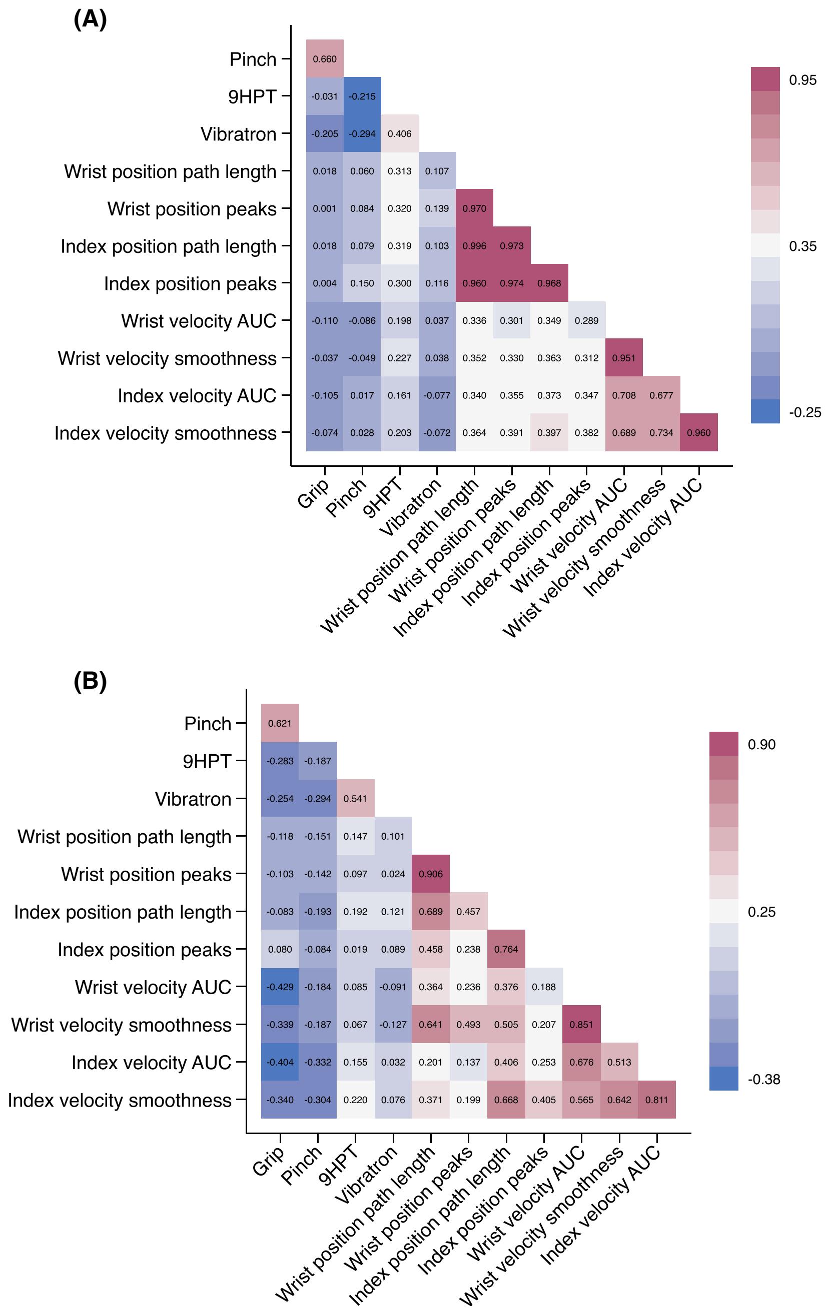

Figure 4. Spearman's correlation coefficients heatmap, brushing task. Darker pink colors indicate *r* values closer to 1, and darker blue colors indicate values closer to −1. (A) Brushing dominant hand (B) brushing nondominant hand.

Video correlates of poor motor control

Greater path of wrist movement while buttoning in the nondominant hand was correlated with both measures poor motor control (difficulty with purposeful, coordinated movements[25]), that is, long 9HPT time and low pinch strength, as well as diminished vibration sense (high threshold of detection) (Fig. 5B). Motor control showed moderate correlations with video metrics from the eating and brushing tasks.

Association with patient-perceived dysfunction

Self-reported difficulty in pinch (e.g., fastening a zipper) and grip strength (e.g., opening a jar) on the ABILHAND questionnaire showed stronger associations with buttoning

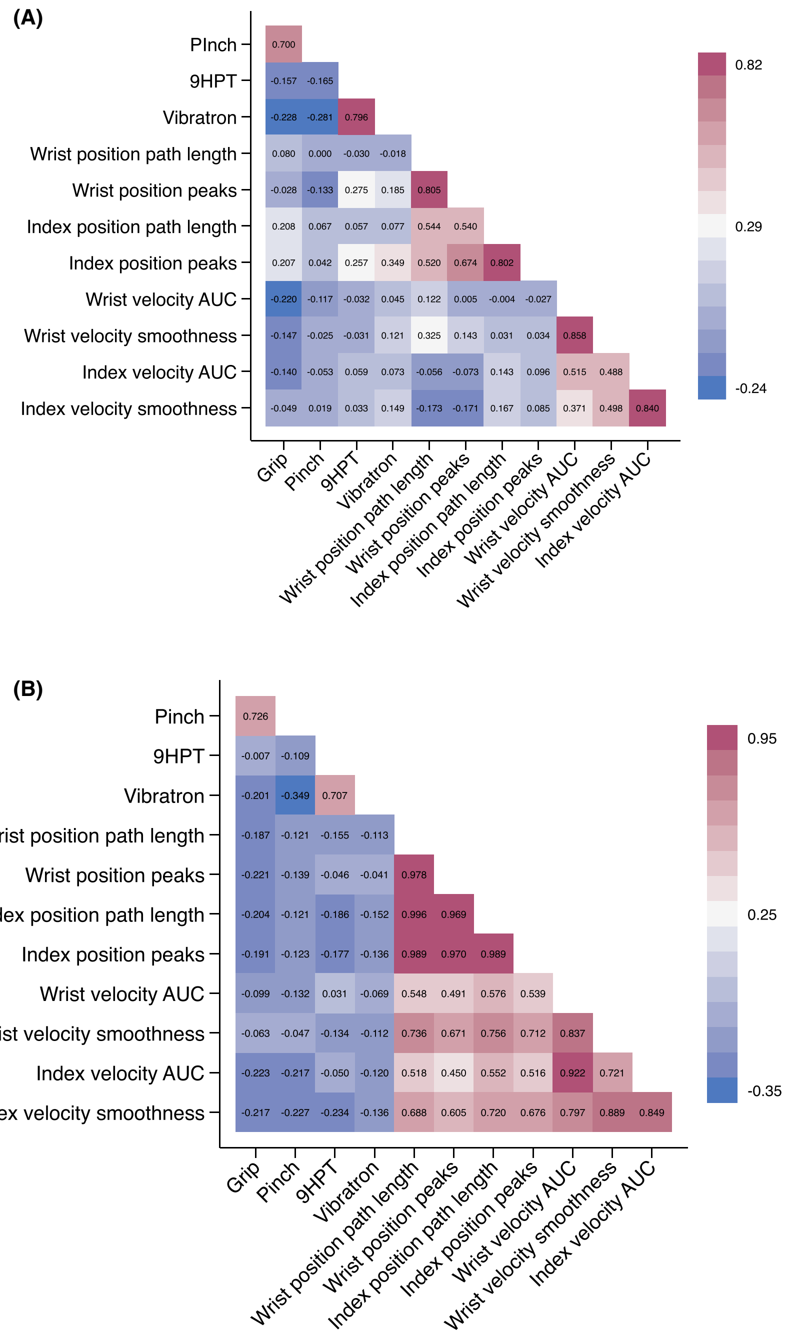

Figure 5. Spearman's correlation coefficients heatmap, eating task. Darker pink colors indicate r values closer to 1, and darker blue colors indicate values closer to −1. (A) Eating dominant hand (B) eating nondominant hand.

video measures than with the in-clinic 9HPT. For example, self-reported difficulty with pinch showed no correlation with 9HPT (Spearman $r = 0.02$, $P = 0.91$), but moderate correlations with wrist position path length ($r = -0.48$, $P = 0.05$), wrist velocity area under the curve ($r = -0.47$, $P = 0.05$), and wrist velocity smoothness ($r = -0.48$, $P = 0.05$) while buttoning.

Test–retest reliability

For the 44 participants providing data on consecutive weeks during the first month of the study, metrics for all tasks resulted in ICC > 0.75, indicating high consistency between repeated measures within 1 week.[26] The smallest real difference (SRD), defined at the 95% confidence limit of the standard error of measurement (SEM) was 13.12% across video metrics.[26] The SRD for each metric is listed in Table S5.

Longitudinal validation of video metrics over 6 months (N = 37)

Clinical measures

Over the 6 month study, mean 9HPT only decreased by 2.7 sec for the dominant hand (P = 0.11) and 2.4 sec for the nondominant hand (P = 0.52); 6 participants (15%) had 9HPT scores that changed ≥20% in the dominant hand and 4 (10%) who changed in the nondominant hand.[27] A marginal reduction in pinch strength was noted (mean change dominant hand: 0.8 kg/cm^2, P = 0.05; nondominant hand: 0.6 kg/cm^2, P = 0.16), as well as in the ABILHAND pinch subscore (P = 0.05) but not the grasp subscore. Of the 13 participants whose pinch strength worsened in both hands over 6 months, ABILHAND self-reported pinch subscore worsened for 11. Grip strength and vibration were stable over the study period (Table S4).

Video measures

Based on the strong correlations with 9HPT and with self-reported impairment in the cross-sectional analyses, the buttoning task was selected for the longitudinal analyses. Most metrics derived from each hand showed statistically significant worsening over the 6 months (Table 2). This includes wrist path position (dominant: P = 0.04, nondominant: P = 0.05), wrist position peaks (dominant: P = 0.01, nondominant: P = 0.02), wrist velocity smoothness (dominant: P = 0.01), and position peaks of the index finger (dominant: P = 0.02, nondominant: P = 0.04).

Table 2. Changes in 9HPT and in video metrics derived from buttoning tasks over 6 months (N = 37).

Outcome	Mean difference	Smallest real difference	95% CI	P-value
9HPT				
Dominant	−1.93		−4.01 to 7.87	0.51
Nondominant	−4.99		−11.30 to 1.31	0.11
Buttoning task				
Wrist position AUC				
Dominant	−0.03	0.98	−0.12 to 0.07	0.54
Nondominant	0.07	0.01	−0.04 to 0.19	0.19
Wrist position path length				
Dominant	−1.50	0.62	−2.94 to −0.07	0.04*
Nondominant	−1.73	0.71	−3.61 to 0.14	0.05*
Wrist position peaks				
Dominant	−2.57	0.28	−5.91 to 0.77	0.01*
Nondominant	−2.00	0.64	−5.36 to 1.35	0.02*
Wrist velocity AUC				
Dominant	0.03	0.66	−0.01 to 0.06	0.15
Nondominant	−0.01	0.04	−0.11 to 0.09	0.83
Wrist velocity smoothness				
Dominant	0.03	0.61	−0.008 to 0.07	0.01*
Nondominant	−0.006	0.01	−0.11 to 0.10	0.09
Index position AUC				
Dominant	−0.03	0.19	−0.13 to 0.06	0.48
Nondominant	0.07	0.20	−0.04 to 0.17	0.18
Index position path length				
Dominant	−1.28	0.76	−3.23 to 0.67	0.18
Nondominant	−1.60	0.85	−3.57 to 0.37	0.10
Index position peaks				
Dominant	−4.29	0.47	−7.87 to −0.69	0.02*
Nondominant	−3.14	0.78	−6.23 to −0.06	0.04*
Index velocity AUC				
Dominant	0.02	0.05	−0.05 to 0.08	0.52
Nondominant	0.01	0.04	−0.04 to 0.06	0.61
Index velocity smoothness				
Dominant	0.03	0.14	−0.04 to 0.09	0.41
Nondominant	0.02	0.03	−0.04 to 0.07	0.55

9HPT, 9 hole peg test; AUC, area under the curve.
*Indicates P < 0.05.

Comparative sensitivity to change: clinical versus buttoning video metrics

Overall, all 37 participants worsened in dexterity, assessed as continuous measures over the study. In the dominant hand, 45% of participants changed by video metrics alone, 35% by both video metrics and 9HPT and 10% by 9HPT alone. The remaining 5% of participants did not change on either metric. This trend was similar in the nondominant hand: 50% of participants changed by video metrics alone, 20% by both video metrics and 9HPT, and 15% by 9HPT alone.

"When change was measured categorically by worsening on buttoning video metrics by the SRD95, Table 2, in the dominant hand 65% of participants changed by buttoning video metrics alone, 10% by both video metrics and 9HPT, and 5% by 9HPT alone. The remaining 20% of participants did not change on either metric. Similarly in the nondominant hand, 65% of participants categorically changed by buttoning video metrics alone, 10% by both video metrics and 9HPT, and 5% by 9HPT alone (Fig. 6). However, the same trends in categorical change (by the SRD95) were not seen for the brushing and eating tasks (Figure S1)."

Discussion

Detecting subtle changes in dexterity has monitoring and treatment implications across many neurological diseases, as well as for the healthy aging population.[28] The current study sought to overcome limitations of existing in-clinic

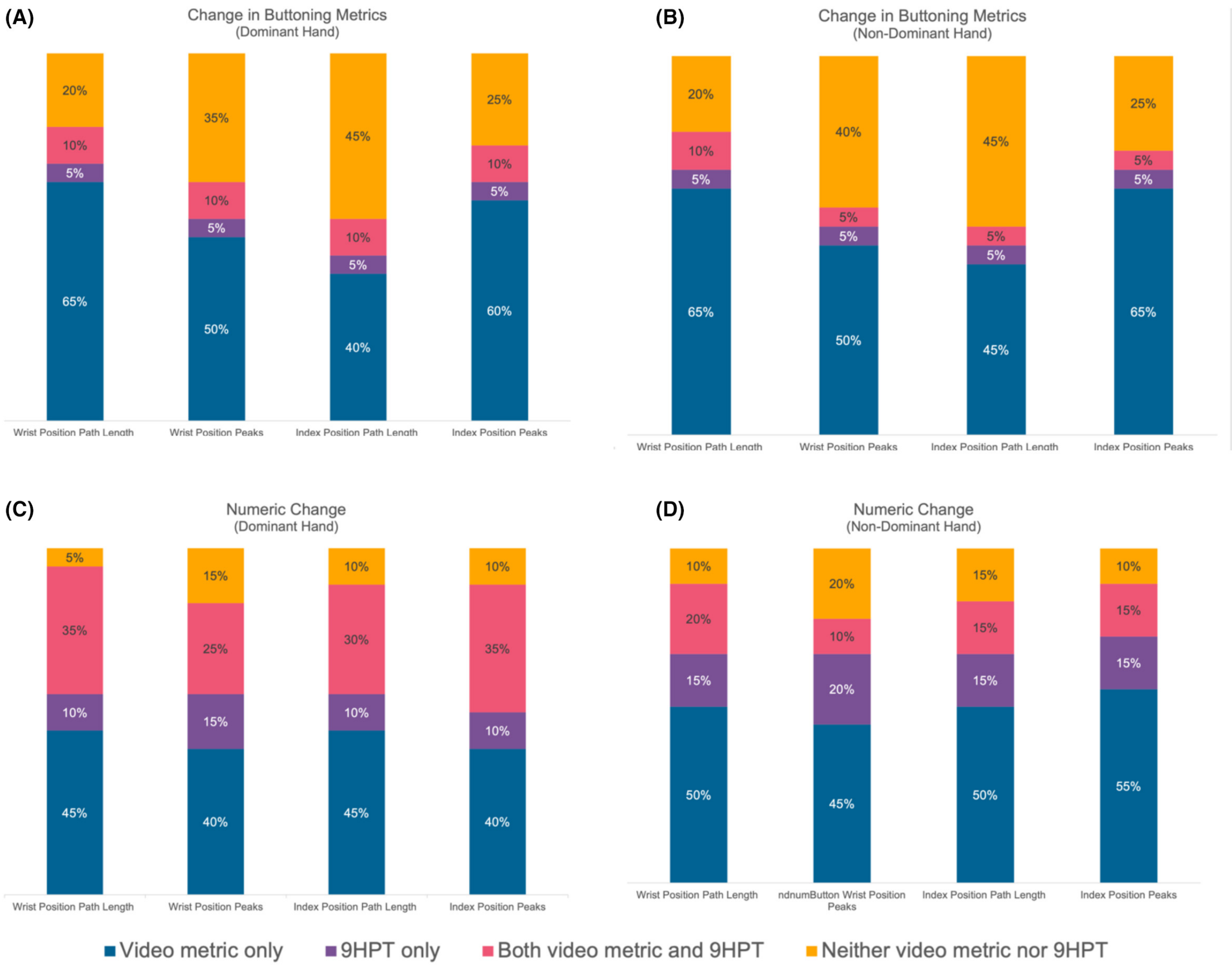

Figure 6. Sensitivity of 9HPT and buttoning video metrics in change detection over study period. Video measures are more sensitive to changes over 6 months than 9HPT. Both categorical 20% change, as well as continuous change, were more commonly detected using video metric than 9HPT scores.

and remote tools by evaluating a novel form of data collection: patient-generated videos of themselves performing ecologically valid ADLs. In an MS population, this low-cost, low-technology solution was feasible, with high satisfaction and adherence and low barriers to completion.

In proof-of-concept analyses, measures extracted from the buttoning videos correlated highly with the in-clinic 9HPT (and better with self-reported dexterity problems) but were more sensitive to worsening over 6 months despite this being a low disability cohort where only 47% categorically worsened by the 13.12% SRM on video metrics. The relatively weaker associations and 6-month stability found for brushing and eating tasks are likely due to the larger, gross motor movements required relative to the finer motor abilities required for buttoning and the 9HPT. Buttoning requires the most pinch strength, and given its correlation with vibration sensation, also invokes the importance of dorsal column sensory pathway integrity for manipulating buttons. The buttoning task examined in this study evaluated both gross and fine movements required to complete the movement—subsequent work should explore the distinctions between various phases of the task in order to develop a more robust assessment to evaluate pinch strength. Further assessments of validity included an independent validation cohort of 35 additional participants with similar 9HPT scores, where again the buttoning task resulted in statistically significant correlations. The stability and replicability of these results speaks to this method's promise and high clinical validity.

The higher correlations between the patient-reported functional impairments and video measures suggest that they better reflect patient functional capacities than the clinical tests. In fact, most rehabilitation efforts focus on *capacity* measures (what someone reports they are capable of doing, e.g., ABILHAND), though patients seek out rehabilitation services to improve *performance* in their daily, unstructured lives.[29] Patient-generated videos allow for more direct measurement of movement during tasks in a natural environment, better reflecting performance. Further, identifying the more detailed *aspects* of movement that changed in the video metrics (e.g., speed, distance traveled) could allow clinicians to better understand and target the extent of functional challenges a patient is experiencing.

The current study advances remote research for neurological populations by demonstrating the feasibility and meaningfulness of patient-uploaded videos. Videos provide powerful assessments of movement, and patient-uploaded, in-home videos provide substantial accessibility benefits over videos collected under more controlled in-clinic conditions. Intuitively, uploading “selfies” is near-ubiquitous in modern-day life, and is a technology familiar to many. According to 2019 data, 85% of adult Americans own a smartphone,[30] including all potential participants referred to the current study (with 44% smartphones being manufactures in 2018 or prior). This “bring your own device” approach to functional assessments overcomes some limitations of other customized digital health approaches (e.g., wearable devices, computerized keyboards, smartphone, and tablet-based applications, video conferencing with clinicians), in that it is cost-effective, uses consumer-grade video software both encoded and regularly maintained in most smartphones, and does not require the purchase of hardware. Overall, 95% participants submitted videos that could be analyzed, without any guidance or supervision; and baseline dexterity did not influence their ability to upload high-quality videos and complete assessments, which may be due to the relatively low disease burden in this cohort (median EDSS: 3). Further, this method delivers videos directly to the clinical or research group who can generate high quality kinematic data without any programming knowledge. The source videos can also be stored for updated analysis as pose estimation algorithms inevitably improve and become more sensitive to impairment and change. The current proof of concept study warrants replication in larger cohorts of individuals with more advanced disability.

The advantages of capturing change through “self-care selfie videos”—including accessibility, adherence and retention, participant satisfaction, correlation with patient-reported difficulties, and sensitivity to change are particularly beneficial given the often insidious, “silent,” disease progression in people with MS. Users’ satisfaction and perceptions of usability are critical to determining the eventual widespread adoption of a digital tool.[31] Highly specific, easily attainable metrics such as those obtained from the current video analyses could allow clinicians to not only identify limitation in functional activities, but also detect early changes contributing to disease progression and inform rehabilitation protocols. Future applications may include patient-uploaded videos for collection of walking, speech, and other video-amenable data. “Self-care selfies” represent a novel approach to quantify real-time kinematics during real-world ADLs, and this feasible approach could offer benefits across other conditions characterized by loss of hand function (e.g., Parkinson’s disease, amyotrophic lateral sclerosis) including healthy aging.

Author contributions

AG: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing-original draft, visualization. **WOT**: methodology, software, validation, formal analysis, data curation. **IW**: validation, formal analysis. **SP**: visualization. **AB**: formal analysis. **HSS**: writing- review, supervision. **NEF**: conceptualization, writing-review, supervision. **JMG**: conceptualization, writing-review, supervision. **DDA**: conceptualization, writing-review, supervision. **RB**: conceptualization, writing-original draft, writing-review supervision, project administration, funding acquisition.

Acknowledgments

Dr. Riley Bove is funded by the National Multiple Sclerosis Society Harry Weaver Award. This funding source did not play a role in study design; in the collection, analysis, and interpretation of data; in the writing of the report; nor in the decision to submit the paper for publication.

Conflict of Interest

Dr. Riley Bove is the recipient of a National Multiple Sclerosis Harry Weaver Award. She has received research support from the National Multiple Sclerosis Society, the National Institutes of Health, and the Department of Defense. She has also received research support from Biogen, Novartis, and Roche Genentech. She has received personal compensation for consulting from Alexion, EMD Serono, Horizon, Jansen, and TG Therapeutics. She declares no competing interests.

References

1. Smith D. Grasping the importance of our hands. InMotion. Vol 16. Amputee Coalition of America; 2006.
2. Cadden M, Arnett P. Factors associated with employment status in individuals with multiple sclerosis. Int J MS Care. 2015;17(6):284-291.

3. Feys P, Romberg A, Ruutiainen J, Ketelaer P. Interference of upper limb tremor on daily life activities in people with multiple sclerosis. Occup Ther Health Care. 2004;17(3–4):81-95.
4. Fox EJ, Markowitz C, Applebee A, et al. Ocrelizumab reduces progression of upper extremity impairment in patients with primary progressive multiple sclerosis: findings from the phase III randomized ORATORIO trial. Mult Scler J. 2018;24(14):1862-1870.
5. Aghanavesi S, Nyholm D, Senek M, Bergquist F, Memedi M. A smartphone-based system to quantify dexterity in Parkinson's disease patients. Inform. Med. Unlocked. 2017;9:11-17.
6. Wissel BD, Mitsi G, Dwivedi AK, et al. Tablet-based application for objective measurement of motor fluctuations in Parkinson disease. Digit Biomark. 2017;1(2):126-135.
7. Dai H, Cai G, Lin Z, Wang Z, Ye Q. Validation of inertial sensing-based wearable device for tremor and bradykinesia quantification. IEEE J Biomed Health Inform. 2021;25 (4):997-1005.
8. Mahadevan N, Demanuele C, Zhang H, et al. Development of digital biomarkers for resting tremor and bradykinesia using a wrist-worn wearable device. NPJ Digit Med. 2020;3(1):5.
9. Akram N, Li H, Ben-Joseph A, et al. Developing and validating a new web-based tapping test for measuring distal bradykinesia in Parkinson's disease. medRxiv 2020. doi:10.1101/2020.06.30.20141572
10. Matarazzo M, Arroyo-Gallego T, Montero P, et al. Remote monitoring of treatment response in Parkinson's disease: the habit of typing on a computer. Mov Disord. 2019;34 (10):1488-1495.
11. Chen W, Yu C, Tu C, et al. A survey on hand pose estimation with wearable sensors and computer-vision-based methods. Sensors. 2020;20(4):1074.
12. Kidziński Ł, Yang B, Hicks JL, Rajagopal A, Delp SL, Schwartz MH. Deep neural networks enable quantitative movement analysis using single-camera videos. Nat Commun. 2020;11(1):4054.
13. Sato K, Nagashima Y, Mano T, Iwata A, Toda T. Quantifying normal and parkinsonian gait features from home movies: practical application of a deep learning-based 2D pose estimator. PLoS One. 2019;14(11):e0223549.
14. Bae JH, Kang SH, Seo KM, Kim DK, Shin HI, Shin HE. Relationship between grip and pinch strength and activities of daily living in stroke patients. Ann Rehabil Med. 2015;39(5):752-762.
15. Zackowski KM, Wang JI, McGready J, Calabresi PA, Newsome SD. Quantitative sensory and motor measures detect change over time and correlate with walking speed in individuals with multiple sclerosis. Mult Scler Relat Disord. 2015;4(1):67-74.
16. Feys P, Lamers I, Francis G, et al. The Nine-Hole Peg Test as a manual dexterity performance measure for multiple sclerosis. Mult Scler. 2017;23(5):711-720.
17. Harris PA, Taylor R, Thielke R, Payne J, Gonzalez N, Conde JG. Research electronic data capture (REDCap)—a metadata-driven methodology and workflow process for providing translational research informatics support. J Biomed Inform. 2009;42(2):377-381.
18. Barrett LE, Cano SJ, Zajicek JP, Hobart JC. Can the ABILHAND handle manual ability in MS? Mult Scler. 2013;19(6):806-815.
19. Bove R, White CC, Giovannoni G, et al. Evaluating more naturalistic outcome measures: a 1-year smartphone study in multiple sclerosis. Neurol Neuroimmunol Neuroinflamm. 2015;2(6):e162.
20. Edemekong PF, Bomgaars DL, Sukumaran S, Levy SB. Activities of daily living. StatPearls. StatPearls Publishing StatPearls Publishing LLC; 2021.
21. Schnall R, Cho H, Liu J. Health information Technology Usability Evaluation Scale (Health-ITUES) for usability assessment of mobile health technology: validation study. JMIR Mhealth Uhealth. 2018;6(1):e4.
22. Amprimo G, Masi G, Pettiti G, Olmo G, Priano L. Hand tracking for clinical applications: validation of the Google MediaPipe hand (GMH) and the depth-enhanced GMH-D frameworks. bioRxiv 2023.
23. Romeo AR, Rowles WM, Schleimer ES, et al. An electronic, unsupervised patient-reported Expanded Disability Status Scale for multiple sclerosis. Mult Scler. 2021;27(9):1432-1441. doi:10.1177/1352458520968814
24. Lamers I, Cattaneo D, Chen CC, Bertoni R, Van Wijmeersch B, Feys P. Associations of upper limb disability measures on different levels of the international classification of functioning, disability and health in people with multiple sclerosis. Phys Ther. 2015;95 (1):65-75.
25. Latash ML, Levin MF, Scholz JP, Schöner G. Motor control theories and their applications. Medicina (Kaunas). 2010;46(6):382-392.
26. Beckerman H, Roebroeck ME, Lankhorst GJ, Becher JG, Bezemer PD, Verbeek AL. Smallest real difference, a link between reproducibility and responsiveness. Qual Life Res. 2001;10(7):571-578.
27. Koch MW, Repovic P, Mostert J, et al. The nine hole peg test as an outcome measure in progressive MS trials. Mult Scler Relat Disord. 2023;69:104433.
28. García-Hermoso A, Cavero-Redondo I, Ramírez-Vélez R, et al. Muscular strength as a predictor of all-cause mortality in an apparently healthy population: a systematic review and meta-analysis of data from approximately 2 million men and women. Arch Phys Med Rehabil. 2018;99(10):2100-2113.e5.
29. Lang CE, Holleran CL, Strube MJ, et al. Improvement in the capacity for activity versus improvement in performance of activity in daily life during outpatient rehabilitation. J Neurol Phys Ther. 2023;47(1):16-25.

30. Technology PRCIa. Mobile fact sheet. https://www.pewresearch.org/internet/fact-sheet/mobile/. Published 2021. Updated April 7, 2021. Accessed May 13, 202.
31. Wienert J, Zeeb H. Implementing health apps for digital public health – an implementation science approach adopting the consolidated framework for implementation research. Front Public Health. 2021;9:610237.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S1. Video kinematic metrics summary.
Table S2. Validation cohort demographics and baseline characteristics.
Table S3. Responses to monthly feedback surveys.
Table S4. Change in hand function using established clinical and patient-reported measures over 6 months.
Table S5. Changes in 9HPT and in video metrics derived from brushing and eating tasks over 6 months ($N = 37$).
Figure S1. Changes in brushing and eating task video metrics and 9HPT scores over 6 months.

