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Remote, unsupervised functional motor task evaluation in older adults across the United States using the MindCrowd electronic cohort

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Abstract

COVID-19 has impacted the ability to evaluate motor function in older adults, as motor assessments typically require face-to-face interaction. One hundred seventy-seven older adults nationwide completed an unsupervised functional upper-extremity assessment at home. Data were compared to data from an independent sample of community-dwelling older adults (N=250) assessed in lab. The effect of age on performance was similar between the in-lab and at-home groups. Practice effects were also similar. Assessing upper-extremity motor function remotely is feasible and reliable in community-dwelling older adults. This test offers a practical solution for telehealth practice and other research involving remote or geographically isolated individuals.

Keywords

motor; older adult; remote assessment

Introduction

Assessing motor function in older adults is essential, as it is affected by neurologic conditions like stroke (Lang et al., 2013), Mild Cognitive Impairment (MCI) (Jekel et

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COI Statement: In accordance with Taylor & Francis policy and my ethical obligation as a researcher, I am reporting that I, the corresponding author, have submitted an invention disclosure to the Arizona State University Technology Transfer Office and am inquiring about a provisional patent and/or copyright on the materials reported in the enclosed paper. I have disclosed those interests fully to Taylor & Francis, and I have in place an approved plan for managing any future potential conflicts arising from the emerging intellectual property. No companies or commercialization plan exist at this time.

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al., 2015), Parkinson's disease (Roalf et al., 2018) and Alzheimer's disease (Kluger et al., 1997). However, most clinical motor assessments require face-to-face administration and may also require specialized medical equipment (e.g., dynamometry) (Milne & Maule, 1984), while more experimental measures typically use motion capture (Heath et al., 1999; Owings & Grabiner, 2004), robotics (Pearce et al., 2012), or other expensive technologies (e.g., transcranial magnetic stimulation, electromyography, or magnetic resonance imaging) (Ferber et al., 2002; Resnick, 2000; Schambra et al., 2015). Thus, these motor assessments are not feasible in remote contexts and are limited in re-test frequency or longitudinal evaluation due to cost and time constraints. Due to the COVID-19 pandemic, many medical practices and research methods have shifted to remote, internet-based approaches (Klil-Drori et al., 2021; Rowley et al., 2019; Thornton, 2020), and many older adults are unwilling or unable to engage in face-to-face, in-person research (Roe et al., 2021). These issues are barriers to evaluating motor function, tracking disease progression over time, and measuring the efficacy of an intervention as an outcome variable, particularly for older populations who have been encouraged to remain isolated/distanced due to COVID-19. Thus, there is an urgent need for objective motor assessments that are feasible and reliable for remote administration in people's homes.

In light of this and other advances in telehealth, new research has focused on the feasibility, reliability, and validity of remote motor assessment and its relationship with clinical and demographic measures linked to neurodegeneration and aging. For example, for people with Parkinson's disease and other movement disorders, virtual video-based clinical visits are feasible (Bull et al., 2014; Dorsey, Bloem, & Okun, 2020; Larson, Schneider, & Simuni, 2021; Naito et al., 2021), although patient-reported outcomes tend to be more reliable than clinical motor assessments when administered remotely (Tarolli et al., 2020; see also Hoenig et al., 2018). In addition, at-home surveys can help patients accurately estimate the severity of their motor symptoms (Myers et al., 2021). However, the majority of virtual motor assessments still rely on a clinician during or after the visit, which is a limiting factor for telehealth both currently and in the near future. According to projections from the Association of American Medical Colleges (AAMC), the United States is expected to have a shortage of nearly 122,000 physicians by the year 2033 (AAMC, 2020), with geriatric and rural populations being among the most affected (Hing & Hsiao, 2014). To potentially reduce clinician burden, smartphone apps (e.g., Omberg et al., 2021; Zhou et al., 2020), video game consoles (e.g., Synnott, Chen, Nugent, & Moore, 2012), and wearable sensors (e.g., Yu, Xiong, Guo, & Wang, 2016) have been developed to assess movement in a remote, unsupervised way. In particular, wearable sensors (e.g., accelerometers, inertial measurement units) are being used to measure motor deficits in-home after stroke (Del Din, Patel, Cobelli, & Bonato, 2011; Lang, Barth, Holleran, Konrad, & Bland, 2020; Maceira-Elvira, Popa, Schmid, & Hummel, 2019). While these new methods allow for more automated data collection, the availability, accessibility and affordability of such technological devices for assessing motor function currently limit their translation from research to clinical practice. For wearable sensors specifically, the need to wear them throughout the day for several days in a row to capture patterns in motor behavior during daily life (Lang et al., 2020; Ramezani et al., 2019; Wang, Markopoulos, Yu, Chen, & Timmermans, 2017) further limits their widespread use, while app-based assessments may struggle with poor to moderate reliability when compared to paper-based, in-lab versions (John et al., 2021). Both types of remote assessments are computationally intensive for movement feature extraction, and subject to issues such as sensor noise, drift, battery life, and data compression (see Maceira-Elvira et al., 2019).

As a potential solution, a brief, low-cost upper extremity motor task has been developed as a more accessible and affordable assessment (Schaefer et al., 2015). It is fabricated from household items, requires minimal technology (only a stopwatch or timing device), and can be assembled and mailed for <$10. Research on the face-to-face version of the task (administered by an experimenter) has shown that older adult task performance is associated with cognitive status (Hooyman, Malek-Ahmadi, Fauth, & Schaefer, 2021), visuospatial memory (Lingo VanGilder et al., 2019), and a one-year decline in activities of daily living (Schaefer et al., 2020), yet is not subject to sex differences (Hooyman et al., 2021). It is also feasible for stroke (Schaefer et al., 2013), Parkinson's disease (Paul et al., 2020), and MCI (Schaefer et al., 2020; Schaefer & Duff, 2017) populations. These features collectively make this task amenable to a remote, at-home setting, but it has not been validated for such use to date.

To test the reliability of this motor assessment as an unsupervised, at-home tool, we utilized the MindCrowd electronic cohort (Huentelman et al., 2020). MindCrowd is an internet-based platform focused on neuroaging research that has collected participant data via online surveys and a brief cognitive assessment, as well as remote genotyping via mail (Talboom et al., 2019). Thus, the purpose of this study was to leverage the MindCrowd infrastructure to validate a remote, unsupervised version of our motor assessment within an in-home setting. To do so, we utilized a subsample of MindCrowd participants over age 40, and compared their at-home, unsupervised performance to data from an existing in-lab, supervised sample.

Methods

Participants

All participants in this study had no previous history of mental illness, neurologic disease, or injury (i.e., stroke, history of seizures, concussion diagnosis, brain disease, or arthritis of the hands or upper limbs). All participants reported normal visual acuity and absence of any peripheral sensory or motor loss/pathology. Although MindCrowd itself has users worldwide, all participants in this study resided in the United States.

Six hundred seventy-nine participants were recruited to this study via e-mail, which provided an overview of the motor task and the option to agree to participate if interested. If the participant consented (via e-mail), a kit containing the motor task, along with instructions for administration and reporting data, was sent to the mailing address provided by the participant. As of January 2021, 241 kits had been mailed to consented participants, and 177 participants (mean age = 59.13 years +/− 9.18; 132 female) had completed the task and reported their data back to MindCrowd. Thus, ~1/3 of contacted MindCrowd users were willing to participate, ~75% of whom completed the assessment with their dominant and non-dominant hand once consented. In this cohort, hand dominance was self-reported. The WCG Institutional Review Board approved this portion of the study.

The MindCrowd data were then compared to an independent sample that had been previously completed collected in-lab (Hooyman et al., 2021) (N = 250, mean age = 73.12 years +/− 8.22, female = 129). All participants in the in-lab cohort were assessed on their dominant and non-dominant hand and provided written informed consent before participation following the World Medical Association Declaration of Helsinki. The Utah State University and Arizona State University Institutional Review Boards approved this portion of the study. A subset of 106 participants from the in-lab cohort (mean age = 71.29 +/− 8.67, female = 72) also completed three more trials of the motor task with the non-dominant hand to evaluate a practice effect. Hand dominance in this cohort was assessed with the Edinburgh Handedness Inventory (Oldfield, 1971).

Motor task

Details regarding the administration of the motor task have been published previously (Schaefer et al., 2015; Schaefer & Duff, 2015; Schaefer & Hengge, 2016) and are viewable on Open Science Framework (https://osf.io/mebcq/?view_only=ce5d894a2490462ebb87d60222462558). Importantly, this task has been related to measures of daily functioning in older adults (Schaefer et al., 2020), demonstrating its ecological validity. Briefly, task performance involved 15 repetitions of acquiring and transporting two kidney beans (~$0.5cm^3$) at a time with a standard plastic spoon from a plastic 'home' cup (9.5 cm in diameter and 5.8 cm in height) to one of three 'target' cups that were the same size as the home container. The target containers were secured radially around the home container at −40°, 0°, and 40° at 16 cm. At the start of the trial, thirty beans were placed into the home cup (15 repetitions x 2 beans/rep). To replicate the experimental set-up at home, individual kits were mailed that had 4 cups, 30 beans, a spoon, written instructions, and a paper 'gameboard' that provided a visual of where the home and target containers should be placed relative to their body, along with tape adhesive to adhere the gameboard to a table while seated. Figure 1 illustrates an assembled view of the task. Participants started by reaching to the left target cup, then returned to the central cup to acquire two more beans to transport to the middle target cup, then the right target cup, and then repeated this 3-cup sequence five times for a total of 15 reaches. The trial ended once the last two beans were deposited into the last cup. Performance was measured as the amount of time it took to complete all 15 reaches, i.e., 'trial time.' Four trials were completed with the non-dominant hand (to evaluate a practice effect), and one trial was performed with the dominant hand. This is because the dominant hand tends to be significantly faster than the non-dominant hand, making it susceptible to a ceiling effect and unlikely to show any practice effect (Schaefer, 2015). MindCrowd participants either timed themselves (61%) or were timed by a partner (39%), while an experimenter timed the in-lab participants.

Statistical analyses

All analyses were performed in R (v4.0.0). To determine the reliability of the assessment, we performed a general linear model with task performance (i.e., trial time) as the dependent variable; group (MindCrowd vs. in-lab), sex, age, and hand were included as independent variables. Given the discrepancy in age ranges between the two groups, we also tested for a group-by-age interaction to determine if this age discrepancy influenced the relationship between group and task performance. Since the non-dominant hand performed four trials overall, only the first trial was used in this first analysis. To determine the similarity in practice effects of the non-dominant hand between MindCrowd and in-lab groups, we performed an autoregressive linear mixed-effects model with performance of the non-dominant hand across the four trials as the dependent variable, and trial number (1–4), group, age, and sex as fixed effects and random intercepts on the participant.

Results

The general linear model showed no significant effect of group (MindCrowd vs. in-lab) on task performance (p=.2), indicating that data collected in-lab by an experimenter was comparable to data collected at home by the participant unsupervised. For example, the mean difference in task performance between in-lab and MindCrowd groups was only ~2% (1.3 seconds). The group-by-age interaction was also not significant (p=.4), indicating the difference in age range between the MindCrowd and in-lab cohorts did not have an effect on task performance. Regardless of group, there was a positive relationship between age and task performance (β_{age}=.29, p<.0001, 95% CI=[.2, .38]), consistent with (Spedden et al., 2017). There was also an effect of hand dominance on task performance ($\beta_{dominantHand}$=−8.62, p<.0001, 95% CI=[−9.46, −7.78]), consistent with previous data showing that the dominant hand is faster (Schaefer, 2015). Dominant and non-dominant hand performance is shown in Figure 2A and B, respectively, for each group. Since the non-dominant hand performed four trials to evaluate practice effects (see below), Figure 2B shows the first trial only. Furthermore, there was also no effect of sex on task performance (β_{Sex}=1.21, p=.17, 95% CI=[−.51, 2.94]), again consistent with previous data (Hooyman et al., 2021). Within the MindCrowd cohort, there was no significant effect on task performance based on whether participants timed themselves or were timed by someone else (mean non-dominant hand difference = 2.6 seconds, 95% CI=[−1.7, 6.4], p=.18; mean dominant hand difference=.51 seconds, 95% CI=[−1.6, 2.7], p=.65). These results collectively show that age (and hand used) impact task performance as we have shown previously, while the location and level of task supervision do not.

The autoregressive linear mixed-effects model also exhibited no effect of group on practice effects when the task is completed multiple times with the non-dominant hand (p=.12) (Fig. 3). Consistent with earlier data, there was a significant effect of the trial (i.e., participants improved with practice) (β_{trial}=−1.8, p<.0001, 95% CI= [−2.27, −1.32]), but these results indicate that improvements in the motor task due to repeated exposure were also not dependent on location or level of supervision.

Discussion

The purpose of this study was to validate a remote, unsupervised version of a functional motor assessment within an in-home setting. Results showed that motor performance collected in-home without supervision was not significantly different from data collected face-to-face in a laboratory setting. In other words, task performance and corresponding practice effects that were measured in the home (either by the participants themselves or by a partner) were not statistically different from those measured in the lab. This suggests that, in contrast to current options for remote motor assessment, older adults nationwide can reliably perform this motor task without supervision or clinical oversight, and without extensive need or reliance on technology (e.g., sensors or smartphone apps).

The feasibility and reliability reported here demonstrate measurable benefits for preclinical research in older adults. First, once participants consented to participate and the kits were mailed, it took only 174 days for all 177 participants to perform the task and report their data. This rate is >1 participant a day, including weekends, whereas the rate of recruitment/participation in a face-to-face research study is often much slower, even before the COVID-19 pandemic. Second, the low cost and simplicity of the individual task components (e.g., beans, plastic spoon) allowed motor data to be collected from all over the United States. As shown in Figure 4, data were collected from participants in 33 different states, a paradigm much different than what is feasible in other single-site studies that involve face-to-face assessments. In addition, this figure illustrates the breakdown of participation by state, relative to how many participants were contacted. We note, however, that the variation in recruitment by state was not part of this study, but was instead simply an administrative by-product of using MindCrowd itself. Findings from this study are encouraging, given that people across the country were willing and able to participate in this study. The ability to collect across a geographically distributed sample can make research more inclusive, particularly for older adults who cannot drive or who do not have access to reliable public transportation (Park et al., 2010). Third, social isolation (due to the COVID-19 pandemic or otherwise) can substantially affect depression and psychological distress among older adults (Gorenko et al., 2021); thus, gerontological research must continue pursuing ways to engage and assess isolated older adults. Lastly, the feasibility and reliability of assessing motor function at home and unsupervised offers new avenues for Alzheimer's disease screening and clinical trial enrichment. Performance on the motor task used here has been linked to visuospatial processes (Lingo VanGilder et al., 2018, 2019), which have been shown to decline earlier than memory scores in cases of eventual Mild Cognitive Impairment (MCI) diagnosis (Johnson, Storandt, Morris, & Galvin, 2009; Mitolo et al., 2013; Rizzo, Anderson, Dawson, & Nawrot, 2000); thus, this task has potential to screen for asymptomatic older adults who may be at risk for developing dementia. Performance on this motor task has also been shown to improve the prediction of eventual functional decline in confirmed MCI (Schaefer et al., 2020). The remote version of this task would allow researchers or clinicians to monitor or screen individuals easily, regardless of geographical location, for study enrollment or neuropsychological follow-up.

One key finding from this study is the reliability of the practice effect for this motor task (see Fig. 3), even when assessed remotely and unsupervised. In general, a practice effect is present when performance on a task/assessment improves as a function of repeated exposure (Calamia, Markon, & Tranel, 2012). Although practice effects have historically been viewed as a nuisance variable, research has shown that practice effects on cognitive assessments have diagnostic and prognostic value for Mild Cognitive Impairment and Alzheimer's disease (Duff, Callister, Dennett, & Tometich, 2012). In other words, the extent to which one's score changes (or does not change) over repeated trials of a cognitive assessment may be better at classifying and predicting cognitive impairment than a single trial of that assessment (Duff et al., 2007; Duff et al., 2011), since practice effects are thought to reflect cognitive reserve and flexibility (Suchy, Kraybill, & Franchow, 2011). However, such practice effects have only been studied in-lab/in-clinic, and have not been tested for reliability in virtual or unsupervised settings. As the general concept of practice effects continues to become popular, it is important to consider practice effects in other types of assessments, including motor assessments like the one presented here, as they may have additional clinical utility for neuropsychologists specifically (Schaefer, Duff, Hooyman, & Hoffman, 2021; Schaefer, Malek-Ahmadi, Hooyman, King, & Duff, 2021). This motor task is less susceptible to a ceiling effect than other existing upper-extremity motor assessments like maximal grip strength via dynamometry (Dixon et al., 2005; Hogrel et al., 2020), the 9-Hole Peg Test (Solaro et al., 2019), or the Fugl-Meyer (Gladstone, Danells, & Black, 2002), particularly when the motor task is completed with the non-dominant hand (see Fig. 3). Recent research suggests that complex movements of the non-dominant hand are more sensitive to white matter hyperintensities within the aging brain (more so than movements of the dominant hand, and more so than simpler movements like finger tapping) (Riaz et al., 2021), which may be a plausible explanation for the observed relationship between task performance and age in this study (see Fig. 2). This is consistent with previous work showing that this motor assessment is more sensitive than grip dynamometry (i.e., grip strength) to cognitive status (Hooyman et al., 2021). Thus, the motor task presented here may be a valid, reliable way to assess motor function remotely, as well as to measure motor practice effects as a proxy for motor learning (Schaefer & Duff, 2015).

Another unique feature of this study is its leveraging of an electronic cohort (MindCrowd). Electronic cohorts allow for more extensive data to be collected from more distributed samples, as evidence by Figure 4. MindCrowd has collected a number of demographic, health, and lifestyle variables on its users (see Talboom et al., 2019), although very few of these have been included in the analyses presented here because of limitations in the in-lab sample. In fact, all shared data elements (e.g., age, sex) between the two cohorts were included in the analyses to consider as many covariates as possible. While this is a limitation of this study, this highlights the advantage of leveraging electronic cohorts for human subjects research. They allow for more extensive and distributed samples and enable a much more robust set of data to be collected than typical face-to-face laboratory research. With the remote version of this motor assessment validated, future studies can investigate how other demographic and health factors affect motor function and motor decline in older adults. There is evidence from previous work suggesting that race/ethnicity (John et al., 2021), socioeconomic status (Schuz, Brick, Wilding, & Conner, 2020), occupation (Darweesh et al., 2018), marital status (Chen & Mok, 2018), co-morbidities (Smith, Hay, Campbell, & Trollor, 2011), polypharmacology (Airagnes, Pelissolo, Lavallee, Flament, & Limosin, 2016), and genetics (Tang et al., 1998) all may interact with each other while influencing performance on complex motor tasks.

To summarize, this study showed that this motor assessment could feasibly and reliably be collected remotely without supervision in older adults. We demonstrate that individuals across a range of geographical locations and ages were willing to participate in a study that involved the assembly, completion, and reporting of a task.

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References

AAMC. (2020). The Complexities of Physician Supply and Demand: Projections From 2018 to 2033. Association of American Medical Colleges

Airagnes G, Pelissolo A, Lavallee M, Flament M, & Limosin F (2016). Benzodiazepine Misuse in the Elderly: Risk Factors, Consequences, and Management. Curr Psychiatry Rep, 18(10), 89. doi:10.1007/s11920-016-0727-9 [PubMed: 27549604]

Bull MT, Darwin K, Venkataraman V, Wagner J, Beck CA, Dorsey ER, & Biglan KM (2014). A pilot study of virtual visits in Huntington disease. J Huntingtons Dis, 3(2), 189–195. doi:10.3233/JHD-140102 [PubMed: 25062861]

Calamia M, Markon K, & Tranel D (2012). Scoring higher the second time around: meta-analyses of practice effects in neuropsychological assessment. Clin Neuropsychol, 26(4), 543–570. doi:10.1080/13854046.2012.680913 [PubMed: 22540222]

Chen C, & Mok VCT (2018). Marriage and risk of dementia: systematic review and meta-analysis of observational studies. J Neurol Neurosurg Psychiatry, 89(3), 227. doi:10.1136/jnnp-2017-317178 [PubMed: 29183958]

Darweesh SKL, Ikram MK, Faber MJ, de Vries NM, Haaxma CA, Hofman A, … Ikram MA (2018). Professional occupation and the risk of Parkinson's disease. Eur J Neurol, 25(12), 1470–1476. doi:10.1111/ene.13752 [PubMed: 30007105]

Del Din S, Patel S, Cobelli C, & Bonato P (2011). Estimating Fugl-Meyer clinical scores in stroke survivors using wearable sensors. Annu Int Conf IEEE Eng Med Biol Soc, 2011, 5839–5842. doi:10.1109/IEMBS.2011.6091444 [PubMed: 22255667]

Dixon WG, Lunt M, Pye SR, Reeve J, Felsenberg D, Silman AJ, … European Prospective Osteoporosis Study, G. (2005). Low grip strength is associated with bone mineral density and vertebral fracture in women. Rheumatology (Oxford), 44(5), 642–646. doi:10.1093/rheumatology/keh569 [PubMed: 15728415]

Dorsey ER, Bloem BR, & Okun MS (2020). A New Day: The Role of Telemedicine in Reshaping Care for Persons With Movement Disorders. Mov Disord, 35(11), 1897–1902. doi:10.1002/mds.28296 [PubMed: 32870517]

Duff K, Beglinger LJ, Schultz SK, Moser DJ, McCaffrey RJ, Haase RF, … Huntington's Study, G. (2007). Practice effects in the prediction of long-term cognitive outcome in three patient samples: a novel prognostic index. Arch Clin Neuropsychol, 22(1), 15–24. doi:10.1016/j.acn.2006.08.013 [PubMed: 17142007]

Duff K, Callister C, Dennett K, & Tometich D (2012). Practice effects: a unique cognitive variable. Clin Neuropsychol, 26(7), 1117–1127. doi:10.1080/13854046.2012.722685 [PubMed: 23020261]

Duff K, Lyketsos CG, Beglinger LJ, Chelune G, Moser DJ, Arndt S, … McCaffrey RJ (2011). Practice effects predict cognitive outcome in amnestic mild cognitive impairment. Am J Geriatr Psychiatry, 19(11), 932–939. doi:10.1097/JGP.0b013e318209dd3a [PubMed: 22024617]

Ferber R, Osternig LR, & Gravelle DC (2002). Effect of PNF stretch techniques on knee flexor muscle EMG activity in older adults. Journal of Electromyography and Kinesiology, 12(5), 391–397. 10.1016/S1050-6411(02)00047-0 [PubMed: 12223172]

Gladstone DJ, Danells CJ, & Black SE (2002). The fugl-meyer assessment of motor recovery after stroke: a critical review of its measurement properties. Neurorehabil Neural Repair, 16(3), 232–240. doi:10.1177/154596802401105171 [PubMed: 12234086]

Gorenko JA, Moran C, Flynn M, Dobson K, & Konnert C (2021). Social Isolation and Psychological Distress Among Older Adults Related to COVID-19: A Narrative Review of Remotely-Delivered Interventions and Recommendations. Journal of Applied Gerontology (Vol. 40, Issue 1, pp. 3–13). SAGE Publications Inc. 10.1177/0733464820958550 [PubMed: 32914668]

Heath M, Roy EA, & Weir PL (1999). Visual-motor integration of unexpected sensory events in young and older participants: A kinematic analysis. Developmental Neuropsychology, 16(2), 197–211. 10.1207/S15326942DN1602_4

Hing E, & Hsiao CJ (2014). State variability in supply of office-based primary care providers: United States, 2012. NCHS Data Brief(151), 1–8. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/24813076

Hoenig HM, Amis K, Edmonds C, Morgan MS, Landerman L, & Caves K (2018). Testing fine motor coordination via telehealth: Effects of video characteristics on reliability and validity. J Telemed Telecare, 24(5), 365–372. doi:10.1177/1357633X17700032 [PubMed: 28350283]

Hogrel JY, Decostre V, Ledoux I, de Antonio M, Niks EH, de Groot I, … Servais L (2020). Normalized grip strength is a sensitive outcome measure through all stages of Duchenne muscular dystrophy. J Neurol, 267(7), 2022–2028. doi:10.1007/s00415-020-09800-9 [PubMed: 32206900]

Hooyman A, Malek-Ahmadi M, Fauth EB, & Schaefer SY (2021). Challenging the relationship of grip strength with cognitive status in older adults. Int J Geriatr Psychiatry, 36(3), 433–442. doi:10.1002/gps.5441 [PubMed: 33027842]

Huentelman MJ, Talboom JS, Lewis CR, Chen Z, & Barnes CA (2020). Reinventing Neuroaging Research in the Digital Age. Trends in Neurosciences, 43(1), 17–23. 10.1016/j.tins.2019.11.004 [PubMed: 31848024]

Jekel K, Damian M, Wattmo C, Hausner L, Bullock R, Connelly PJ, Dubois B, Eriksdotter M, Ewers M, Graessel E, Kramberger MG, Law E, Mecocci P, Molinuevo JL, Nygård L, Olde-Rikkert MG, Orgogozo J-M, Pasquier F, Peres K, … Frölich L (2015). Mild cognitive impairment and deficits in instrumental activities of daily living: a systematic review. Alzheimer's Research & Therapy, 7(1), 17. 10.1186/s13195-015-0099-0

John SE, Evans SA, Kim B, Ozgul P, Loring DW, Parker M, … Goldstein FC (2021). Examination of the reliability and feasibility of two smartphone applications to assess executive functioning in racially diverse older adults. Neuropsychol Dev Cogn B Aging Neuropsychol Cogn, 1–19. doi:10.1080/13825585.2021.1962790

Johnson DK, Storandt M, Morris JC, & Galvin JE (2009). Longitudinal study of the transition from healthy aging to Alzheimer disease. Arch Neurol, 66(10), 1254–1259. doi:10.1001/archneurol.2009.158 [PubMed: 19822781]

Klil-Drori S, Phillips N, Fernandez A, Solomon S, Klil-Drori AJ, & Chertkow H (2021). Evaluation of a Telephone Version for the Montreal Cognitive Assessment: Establishing a Cutoff for Normative Data From a Cross-Sectional Study. Journal of Geriatric Psychiatry and Neurology, 089198872110026. 10.1177/08919887211002640

Kluger A, Gianutsos JG, Golomb J, Ferris SH, George AE, Franssen E, & Reisberg B (1997). Patterns of Motor Impairment in Normal Aging, Mild Cognitive Decline, and Early Alzheimer' Disease. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 52B(1), P28–P39. 10.1093/geronb/52B.1.P28

Lang CE, Barth J, Holleran CL, Konrad JD, & Bland MD (2020). Implementation of Wearable Sensing Technology for Movement: Pushing Forward into the Routine Physical Rehabilitation Care Field. Sensors (Basel), 20(20). doi:10.3390/s20205744

Lang CE, Bland MD, Bailey RR, Schaefer SY, & Birkenmeier RL (2013). Assessment of upper extremity impairment, function, and activity after stroke: Foundations for clinical decision making. Journal of Hand Therapy, 26(2), 104–115. 10.1016/j.jht.2012.06.005 [PubMed: 22975740]

Larson DN, Schneider RB, & Simuni T (2021). A New Era: The Growth of Video-Based Visits for Remote Management of Persons with Parkinson's Disease. J Parkinsons Dis, 11(s1), S27–S34. doi:10.3233/JPD-202381 [PubMed: 33492246]

Lingo VanGilder J, Hengge CR, Duff K, & Schaefer SY (2018). Visuospatial function predicts one-week motor skill retention in cognitively intact older adults. Neuroscience Letters, 664, 139–143. 10.1016/j.neulet.2017.11.032 [PubMed: 29154858]

Lingo VanGilder J, Walter CS, Hengge CR, & Schaefer SY (2019). Exploring the relationship between visuospatial function and age-related deficits in motor skill transfer. Aging Clinical and Experimental Research, 1–8. 10.1007/s40520-019-01345-w

Maceira-Elvira P, Popa T, Schmid AC, & Hummel FC (2019). Wearable technology in stroke rehabilitation: towards improved diagnosis and treatment of upper-limb motor impairment. J Neuroeng Rehabil, 16(1), 142. doi:10.1186/s12984-019-0612-y [PubMed: 31744553]

Milne JS, & Maule MM (1984). A Longitudinal Study on Handgrip and Dementia in Older People. Age and Ageing, 13(1), 42–48. 10.1093/ageing/13.1.42 [PubMed: 6702503]

Mitolo M, Gardini S, Fasano F, Crisi G, Pelosi A, Pazzaglia F, & Caffarra P (2013). Visuospatial memory and neuroimaging correlates in mild cognitive impairment. J Alzheimers Dis, 35(1), 75–90. doi:10.3233/JAD-121288 [PubMed: 23357899]

Myers TL, Tarolli CG, Adams JL, Barbano R, Cristina Gil-Diaz M, Spear KL, … Schneider RB (2021). Video-based Parkinson's disease assessments in a nationwide cohort of Fox Insight participants. Clin Park Relat Disord, 4, 100094. doi:10.1016/j.prdoa.2021.100094 [PubMed: 34316671]

Naito A, Wills AM, Tropea TF, Ramirez-Zamora A, Hauser RA, Martino D, … Beck JC (2021). Expediting telehealth use in clinical research studies: recommendations for overcoming barriers in North America. NPJ Parkinsons Dis, 7(1), 34. doi:10.1038/s41531-021-00177-8 [PubMed: 33846349]

Omberg L, Chaibub Neto E, Perumal TM, Pratap A, Tediarjo A, Adams J, … Mangravite LM (2021). Remote smartphone monitoring of Parkinson's disease and individual response to therapy. Nat Biotechnol. doi:10.1038/s41587-021-00974-9

Oldfield RC (1971). The assessment and analysis of handedness: The Edinburgh inventory. Neuropsychologia, 9(1), 97–113. 10.1016/0028-3932(71)90067-4 [PubMed: 5146491]

Owings TM, & Grabiner MD (2004). Variability of step kinematics in young and older adults. Gait and Posture, 20(1), 26–29. 10.1016/S0966-6362(03)00088-2 [PubMed: 15196516]

Park NS, Roff LL, Sun F, Parker MW, Klemmack DL, Sawyer P, & Allman RM (2010). Transportation Difficulty of Black and White Rural Older Adults. Journal of Applied Gerontology : The Official Journal of the Southern Gerontological Society, 29(1), 70–88. 10.1177/0733464809335597 [PubMed: 22068835]

Paul SS, Dibble LE, Olivier GN, Walter C, Duff K, & Schaefer SY (2020). Dopamine replacement improves motor learning of an upper extremity task in people with Parkinson disease. Behavioural Brain Research, 377, 112213. 10.1016/j.bbr.2019.112213 [PubMed: 31526767]

Pearce AJ, Adair B, Miller K, Ozanne E, Said C, Santamaria N, & Morris ME (2012). Robotics to enable older adults to remain living at home. In Journal of Aging Research (Vol. 2012). 10.1155/2012/538169

Ramezani R, Zhang W, Xie Z, Shen J, Elashoff D, Roberts P, … Naeim A (2019). A Combination of Indoor Localization and Wearable Sensor-Based Physical Activity Recognition to Assess Older Patients Undergoing Subacute Rehabilitation: Baseline Study Results. JMIR Mhealth Uhealth, 7(7), e14090. doi:10.2196/14090 [PubMed: 31293244]

Resnick SM (2000). One-year Age Changes in MRI Brain Volumes in Older Adults. Cerebral Cortex, 10(5), 464–472. 10.1093/cercor/10.5.464 [PubMed: 10847596]

Riaz M, Vangberg TR, Vasylenko O, Castro-Chavira S, Gorecka MM, Waterloo K, & Rodriguez-Aranda C (2021). What does hand motor function tell us about our aging brain in association with WMH? Aging Clin Exp Res, 33(6), 1577–1584. doi:10.1007/s40520-020-01683-0 [PubMed: 32860625]

Rizzo M, Anderson SW, Dawson J, & Nawrot M (2000). Vision and cognition in Alzheimer's disease. Neuropsychologia, 38(8), 1157–1169. doi:10.1016/s0028-3932(00)00023-3 [PubMed: 10838150]

Roalf DR, Rupert P, Mechanic-Hamilton D, Brennan L, Duda JE, Weintraub D, Trojanowski JQ, Wolk D, & Moberg PJ (2018). Quantitative assessment of finger tapping characteristics in mild cognitive impairment, Alzheimer's disease, and Parkinson's disease. Journal of Neurology, 265(6), 1365–1375. 10.1007/s00415-018-8841-8 [PubMed: 29619565]

Roe CM, Rosnick CB, Colletta A, & Babulal GM (2021). Reaction to a Pandemic: Social Distancing and Driving Among Older Adults During COVID-19. Journal of Applied Gerontology, 40(3), 263–267. 10.1177/0733464820966516 [PubMed: 33554720]

Rowley TW, Lenz EK, Swartz AM, Miller NE, Maeda H, & Strath SJ (2019). Efficacy of an Individually Tailored, Internet-Mediated Physical Activity Intervention in Older Adults: A Randomized Controlled Trial. Journal of Applied Gerontology, 38(7), 1011–1022. 10.1177/0733464817735396 [PubMed: 29165018]

Schaefer SY (2015). Preserved motor asymmetry in late adulthood: Is measuring chronological age enough? Neuroscience, 294, 51–59. 10.1016/j.neuroscience.2015.03.013 [PubMed: 25772792]

Schaefer SY, Dibble LE, & Duff K (2015). Efficacy and Feasibility of Functional Upper Extremity Task-Specific Training for Older Adults With and Without Cognitive Impairment. Neurorehabilitation and Neural Repair, 29(7), 636–644. 10.1177/1545968314558604 [PubMed: 25416739]

Schaefer SY, & Duff K (2015). Rapid Responsiveness to Practice Predicts Longer-Term Retention of Upper Extremity Motor Skill in Non-Demented Older Adults. Frontiers in Aging Neuroscience, 7, 214. 10.3389/fnagi.2015.00214 [PubMed: 26635601]

Schaefer SY, & Duff K (2017). Within-session and one-week practice effects on a motor task in amnestic mild cognitive impairment. Journal of Clinical and Experimental Neuropsychology, 39(5), 473–484. 10.1080/13803395.2016.1236905 [PubMed: 27690745]

Schaefer SY, & Hengge CR (2016). Testing the concurrent validity of a naturalistic upper extremity reaching task. Experimental Brain Research, 234(1), 229–240. 10.1007/s00221-015-4454-y [PubMed: 26438508]

Schaefer SY, Hooyman A, & Duff K (2020). Using a Timed Motor Task to Predict One-Year Functional Decline in Amnestic Mild Cognitive Impairment. Journal of Alzheimer's Disease, 1–6. 10.3233/JAD-200518

Schaefer SY, Duff K, Hooyman A, & Hoffman JM (2021). Improving prediction of amyloid deposition in Mild Cognitive Impairment with a timed motor task. medRxiv, 2021.2006.2016.21259056.

Schaefer SY, Malek-Ahmadi M, Hooyman A, King JB, & Duff K (2021). Association between motor task acquisition and hippocampal atrophy in amnestic Mild Cognitive Impairment and Alzheimer's disease. medRxiv, 2021.2005.2031.21258061. doi:10.1101/2021.05.31.21258061

Schaefer SY, Patterson CB, & Lang CE (2013). Transfer of Training Between Distinct Motor Tasks After Stroke. Neurorehabilitation and Neural Repair, 27(7), 602–612. 10.1177/1545968313481279 [PubMed: 23549521]

Schambra HM, Ogden RT, Martínez-Hernández IE, Lin X, Chang YB, Rahman A, Edwards DJ, & Krakauer JW (2015). The reliability of repeated TMS measures in older adults and in patients with subacute and chronic stroke. Frontiers in Cellular Neuroscience, 9(september), 335. 10.3389/fncel.2015.00335 [PubMed: 26388729]

Schuz B, Brick C, Wilding S, & Conner M (2020). Socioeconomic Status Moderates the Effects of Health Cognitions on Health Behaviors within Participants: Two Multibehavior Studies. Ann Behav Med, 54(1), 36–48. doi:10.1093/abm/kaz023 [PubMed: 31260512]

Smith E, Hay P, Campbell L, & Trollor JN (2011). A review of the association between obesity and cognitive function across the lifespan: implications for novel approaches to prevention and treatment. Obes Rev, 12(9), 740–755. doi:10.1111/j.1467-789X.2011.00920.x [PubMed: 21991597]

Solaro C, Cattaneo D, Brichetto G, Castelli L, Tacchino A, Gervasoni E, & Prosperini L (2019). Clinical correlates of 9-hole peg test in a large population of people with multiple sclerosis. Mult Scler Relat Disord, 30, 1–8. doi:10.1016/j.msard.2019.01.043 [PubMed: 30710887]

Spedden ME, Malling ASB, Andersen KK, & Jensen BR (2017). Association Between Gross-Motor and Executive Function Depends on Age and Motor Task Complexity. Developmental Neuropsychology, 42(7–8), 495–506. 10.1080/87565641.2017.1399129 [PubMed: 29161178]

Suchy Y, Kraybill ML, & Franchow E (2011). Practice effect and beyond: reaction to novelty as an independent predictor of cognitive decline among older adults. J Int Neuropsychol Soc, 17(1), 101–111. doi:10.1017/S135561771000130X [PubMed: 21073771]

Synnott J, Chen L, Nugent CD, & Moore G (2012). WiiPD--objective home assessment of Parkinson's disease using the Nintendo Wii remote. IEEE Trans Inf Technol Biomed, 16(6), 1304–1312. doi:10.1109/TITB.2012.2215878 [PubMed: 22949085]

Talboom JS, Håberg A, De Both MD, Naymik MA, Schrauwen I, Lewis CR, Bertinelli SF, Hammersland C, Fritz MA, Myers AJ, Hay M, Barnes CA, Glisky E, Ryan L, & Huentelman MJ (2019). Family history of Alzheimer's disease alters cognition and is modified by medical and genetic factors. ELife, 8. 10.7554/eLife.46179

Tang MX, Stern Y, Marder K, Bell K, Gurland B, Lantigua R, … Mayeux R (1998). The APOE-epsilon4 allele and the risk of Alzheimer disease among African Americans, whites, and Hispanics. JAMA, 279(10), 751–755. doi:10.1001/jama.279.10.751 [PubMed: 9508150]

Tarolli CG, Andrzejewski K, Zimmerman GA, Bull M, Goldenthal S, Auinger P, … Simuni T (2020). Feasibility, Reliability, and Value of Remote Video-Based Trial Visits in Parkinson's Disease. J Parkinsons Dis, 10(4), 1779–1786. doi:10.3233/JPD-202163 [PubMed: 32894251]

Thornton J (2020). Covid-19: How coronavirus will change the face of general practice forever. The BMJ (Vol. 368). BMJ Publishing Group. 10.1136/bmj.m1279

Wang Q, Markopoulos P, Yu B, Chen W, & Timmermans A (2017). Interactive wearable systems for upper body rehabilitation: a systematic review. J Neuroeng Rehabil, 14(1), 20. doi:10.1186/s12984-017-0229-y [PubMed: 28284228]

Yu L, Xiong D, Guo L, & Wang J (2016). A remote quantitative Fugl-Meyer assessment framework for stroke patients based on wearable sensor networks. Comput Methods Programs Biomed, 128, 100–110. doi:10.1016/j.cmpb.2016.02.012 [PubMed: 27040835]

Zhou H, Al-Ali F, Wang C, Hamad A, Ibrahim R, Talal T, & Najafi B (2020). Harnessing digital health to objectively assess cognitive impairment in people undergoing hemodialysis process: The Impact of cognitive impairment on mobility performance measured by wearables. PLoS One, 15(4), e0225358. doi:10.1371/journal.pone.0225358 [PubMed: 32310944]

Figure 1.
Example of assembled task kit. Written instructions and link to the video tutorial on task set-up were included.

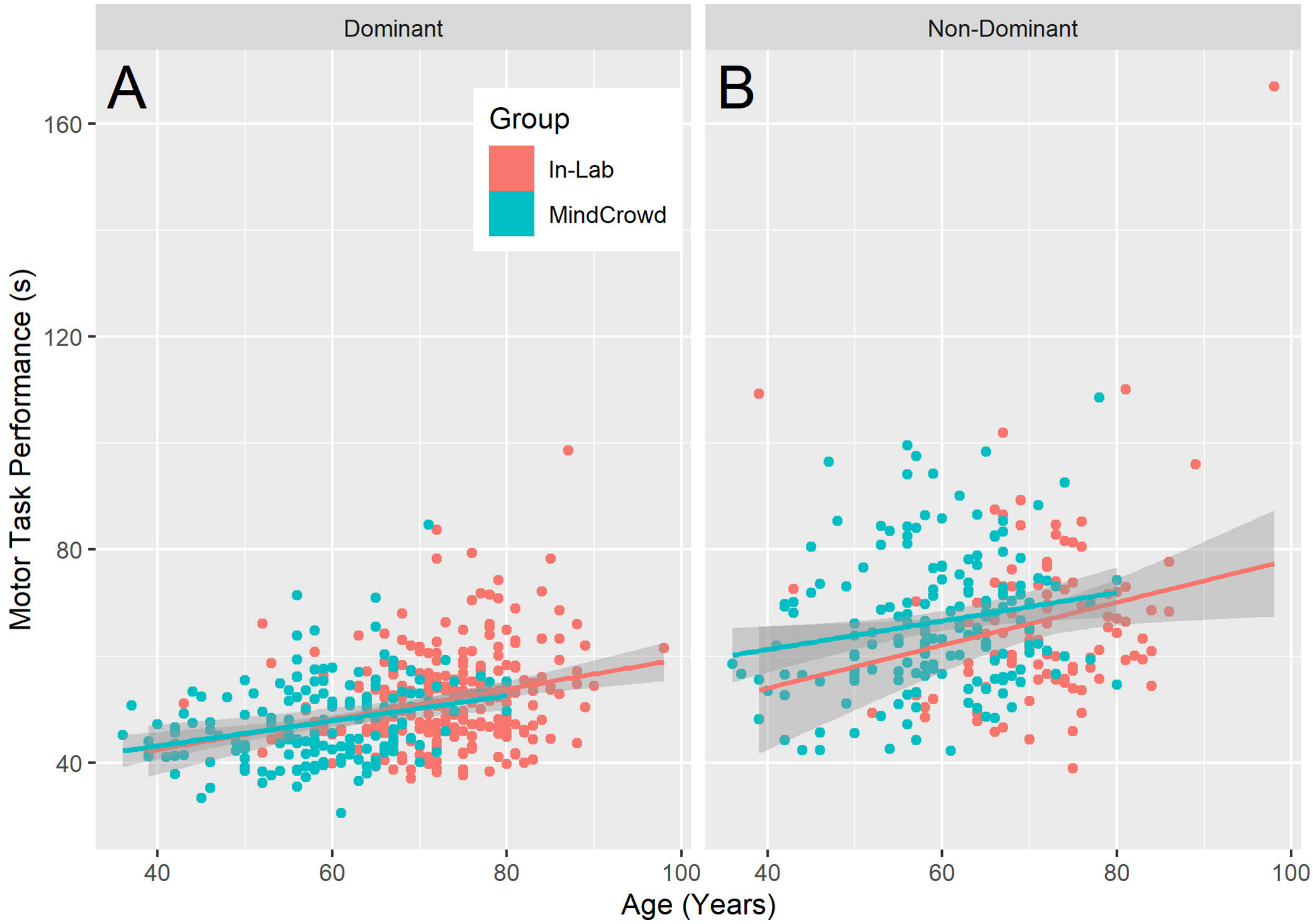

Figure 2.

Relationship between age and motor task performance by group on the first trial: in-lab (pink) vs. MindCrowd (blue); and hand: (A) dominant vs. (B) non-dominant. Gray shading indicates standard error.

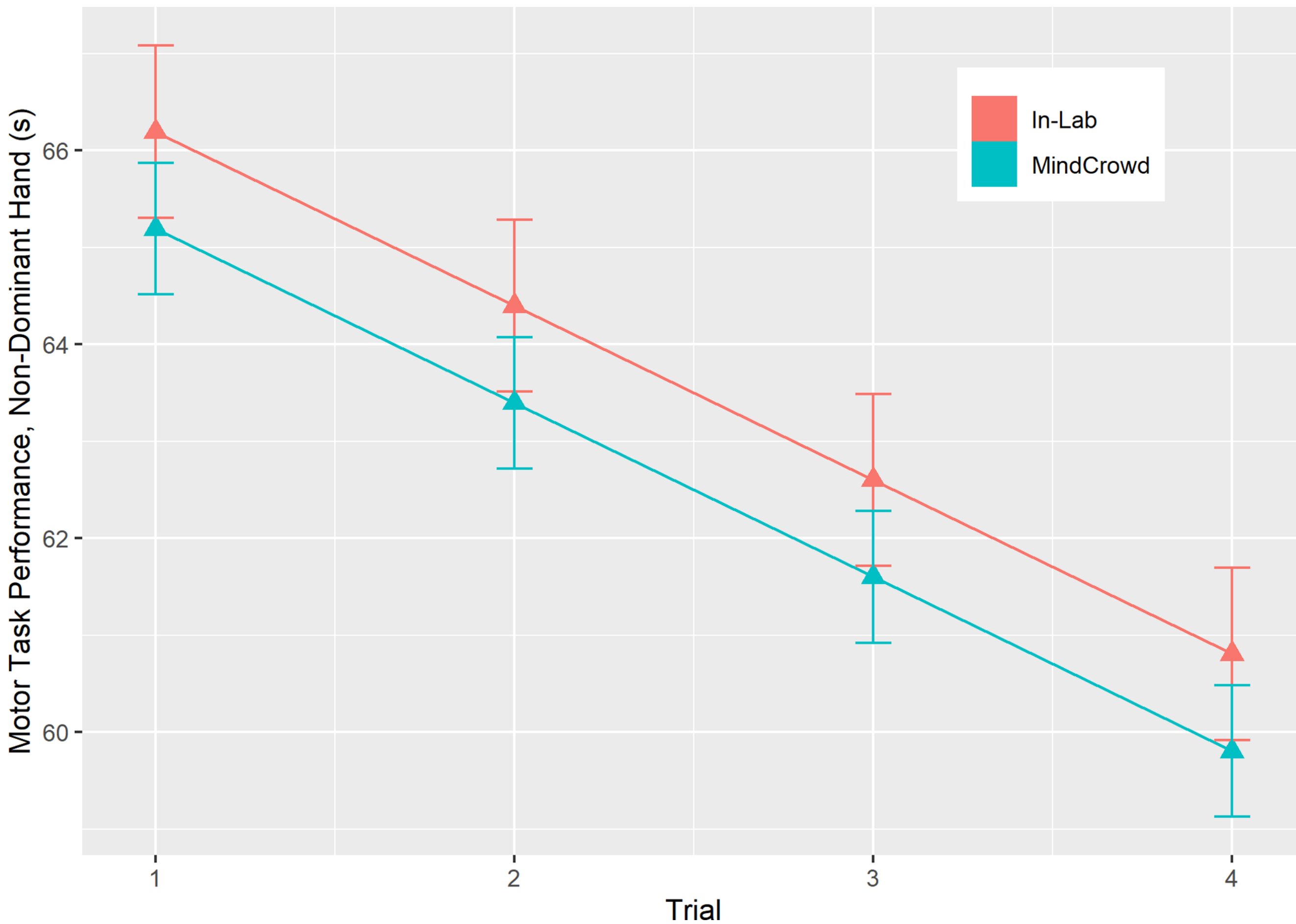

Figure 3.
Estimated trial time of the non-dominant hand across four practice trials calculated from a linear mixed-effects model. In-lab (pink); MindCrowd (blue). Error bars = standard error. Note that the y-axis scale is different here than in Figure 2.

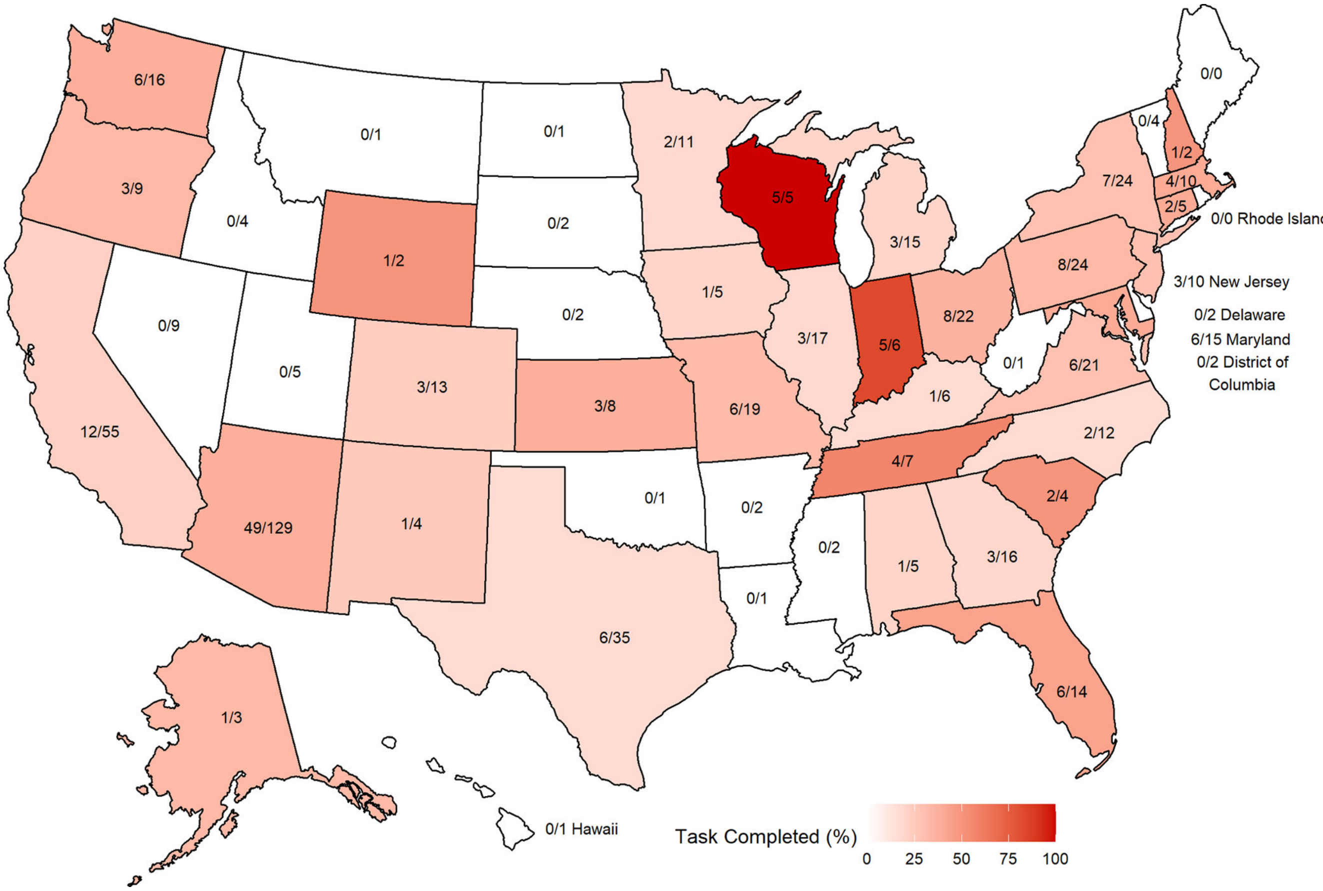

Figure 4.

US map with color intensity showing the ratio (and percentage) of the number of participants who completed the task relative to the number of contacted participants (i.e., those who received an email) per state, with greater color intensity indicating a higher percentage completed. The fraction within each state represents to total number of motor assessments completed (numerator) over the total number of participants contacted (denominator). This figure was generated from the first 589 participants contacted.