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RESEARCH ARTICLE

Cognitive dispersion is related to subtle objective daily functioning changes in older adults with and without cognitive impairment

Alyssa N. De Vito[1,2] | **Catherine H. Ju**[3] | **Samuel Y. Lee**[4] | **Anael Kuperwajs Cohen**[4,5,6] | **Alexandra D. Trofimova**[4,5,6] | **Yan Liu**[7] | **Alyssa Eichten**[4,5,6] | **Adriana Hughes**[4,5,6]

[1]Department of Psychiatry and Human Behavior, Warren Alpert Medical School of Brown University, Providence, Rhode Island, USA

[2]Memory and Aging Program, Butler Hospital, Providence, Rhode Island, USA

[3]Department of Psychology, West Virginia University, Morgantown, West Virginia, USA

[4]Masonic Cancer Center, University of Minnesota, Minneapolis, Minnesota, USA

[5]Department of Psychiatry and Behavioral Sciences, School of Medicine, University of Minnesota Twin Cities, Minneapolis, Minnesota, USA

[6]Minneapolis VA Healthcare System, Minneapolis, Minnesota, USA

[7]School of Public Health, Oregon Health & Science University-Portland State University, Portland, Oregon, USA

Correspondence
Alyssa N. De Vito, Department of Psychiatry and Human Behavior, Warren Alpert Medical School of Brown University, 345 Blackstone Blvd, Providence, RI, USA.
Email: Alyssa_de_vito@brown.edu

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Abstract

Early detection of cognitive and functional decline is difficult given that current tools are insensitive to subtle changes. The present study evaluated whether cognitive dispersion on neuropsychological testing improved prediction of objectively assessed daily functioning using unobtrusive monitoring technologies. Hierarchical linear regression was used to evaluate whether cognitive dispersion added incremental information beyond mean neuropsychological performance in the prediction of objectively assessed IADLs (i.e., computer use, pillbox use, driving) in a sample of 104 community-dwelling older adults without dementia (M_{age} = 74.59, 38.5% Female, 90.4% White). Adjusting for age, sex, education, and mean global cognitive performance, cognitive dispersion improved prediction of average daily computer use duration (R^2 Δ = 0.100, F Change, p = 0.005), computer use duration variability (R^2 Δ = 0.089, F Change p = 0.009), and average daily duration of nighttime driving (R^2 Δ = 0.072, F Change p = 0.013). These results suggest cognitive dispersion may improve prediction of objectively assessed functional changes in older adults without dementia.

KEYWORDS
cognitive variability, daily functioning, mild cognitive impairment, passive monitoring, sensors

1 | BACKGROUND

Alzheimer's disease and Alzheimer's disease-related dementias (AD/ADRDs) currently affect over 6 million Americans and this number is expected to rise to over 13 million by 2060.[1] Recent research suggests that subtle changes in cognition and daily functioning occur several years before the onset of overt clinical impairment.[2,3] Despite this, prevailing diagnostic practices most often identify AD/ADRDs in the mild-to-moderate dementia stage when intervention is less effective.[2] Current tools used to assess cognitive and daily functioning decline are not designed to detect subtle changes that emerge earlier in disease progression making detection in preclinical and prodromal phases of ADRD difficult. Traditional neuropsychological assessment approaches rely on norm-referenced summary scores to detect

cognitive impairment. Alternative scoring approaches such as cognitive dispersion may be more sensitive to early cognitive changes.[4–6] Cognitive dispersion refers to variability in an individual's performance across several domains and has been shown to be associated with informant-reported functional decline.[7]

Emerging evidence suggests that cognitive dispersion may be sensitive to some of the earliest neuropathological changes in AD/ADRD in accordance with the amyloid, tau, and neurodegeneration (ATN) framework. Recent findings have indicated that dispersion is elevated in amyloid-positive individuals and increases in response to tau deposition.[8,9] Bangen and colleagues also found that greater dispersion was linked to medial temporal lobe atrophy in individuals with mild cognitive impairment (MCI).[7] Increases in dispersion over 12 months have also been associated with hypoperfusion in hippocampal and entorhinal cortex among individuals who were biomarker positive (ie, elevated CSF phosphorylated tau 181/Aβ 42 ratio).[10] Cognitive dispersion has been shown to predict diagnostic conversion comparably to well-established cerebrospinal fluid (CSF) biomarkers, suggesting it may be a promising non-invasive alternative for early detection.[11]

Cognitive dispersion has also been shown to be associated with clinical outcomes, including cognitive status and improving prediction of longitudinal disease progression.[6,7,12] However, investigations into the relationship between dispersion and daily functioning have been limited. Dispersion has been previously shown to be associated with an informant-reported decline in functional skills (eg, instrumental activities of daily living [IADLs]) as well as performance on an in-office simulated daily functioning task in a community-dwelling sample of cognitively healthy older adults and those with MCI.[7,13] These preliminary findings suggest that cognitive dispersion may be sensitive to early objective functional change.

Limitations inherent to subjective self and informant ratings (eg, inaccurate and/or biased ratings) have driven interest in objective assessments of IADL functioning. Although simulation tasks have several strengths, they are time-consuming and have reduced ecological validity in comparison to assessments in real-world settings. With dramatic advances in digital technologies, using passive sensors in one's own home environment represents a promising approach to capturing and monitoring subtle daily functioning changes early in the disease spectrum.[2,14–21] Research conducted with passive sensor technologies has demonstrated the ability to detect subtle functional changes in important IADLs such as medication management,[19,20] driving,[18] and computer use[17,21] in older adults with MCI. Despite increasing interest in these technologies, no studies have yet examined the relationship between cognitive dispersion and real-world daily functioning as assessed by passive sensor-based activity monitoring.

This study aimed to evaluate whether cognitive dispersion improved the prediction of real-world functioning assessed using unobtrusive sensors in the home environment above and beyond mean neuropsychological performance in a sample of community-dwelling older adults. We selected nine computer use, driving, and pillbox sensor variables that have previously demonstrated, either (1) group differences between cognitively normal (CN) and MCI participants or are associated with (2) diagnostic conversion to test our hypothesis that including cognitive dispersion in our models would improve prediction of passively assessed IADL performance.

2 | METHODS

2.1 | Participants

Participants were 104 community-dwelling older adults ($M_{age} = 74.59$, 38.5% female, 90.4% White, and $M_{Years\ of\ education} = 15.65$) recruited from the Minneapolis-St. Paul, Minnesota, and Portland, Oregon, metro areas for the Aging Well with Independence using Sensors in the Environment (Aging Well) Study, which was funded by the National Institute on Aging (R01AG058687, PI Hughes) and carried out at the University of Minnesota (UMN), Minneapolis VA Health Care System (MVAHCS), and at Oregon Health & Science University (OHSU) in collaboration with the Oregon Center for Aging & Technology (ORCATECH). The study was approved by the MVAHCS, UMN, and OHSU Institutional Review Boards (IRB numbers 18-00328, 00003177, and 00019378, respectively) and followed all applicable institutional guidelines. All participants provided both written and oral informed consent before enrollment in the study, and participants confirmed comprehension of study procedures by providing a verbal summary to study staff. Participants were required to live independently in their home, take at least one medication daily and agree to use a study-provided pillbox, have a broadband Internet connection, use a home computer at least once per week or be willing to use a study-provided computer, and be considered relatively healthy for their age (no major or uncontrolled medical conditions or major neurological disorders). Participants were also required to have a study partner to answer questionnaires regarding the patient's cognition and daily functioning. Exclusionary criteria included moderate to severe anxiety (Generalized Anxiety Disorder-7 Item score of ≥ 5)[22] or depression (Geriatric Depression Scale-Short Form score of ≥ 7),[23] impaired global cognition (determined by the Montreal Cognitive Assessment [MoCA], total score greater than 2 standard deviations on sex, age, and education adjusted *z*-scores of the National Alzheimer's Coordinating Center [NACC] Uniform Data Set [UDS] norms,[24] or a global Clinical Dementia Rating [CDR] Scale score of >0.5).[25] Participants were classified by the study PI (Hughes) into two groups: CN ($n = 59$) or MCI ($n = 45$) at the baseline study visit using the National Institute on Aging-Alzheimer's Association workgroup comprehensive core clinical criteria for MCI.[26] Specifically, participants were classified as MCI if they had a CDR score of 0.5 and/or had two or more scores neuropsychological scores fall below the ninth percentile. Please see Table 1 for sample demographics.

2.2 | The Aging Well study

The Aging Well Study was a longitudinal observational cohort study that took place between 2018 and 2023. The purpose of this study was to use an innovative remotely monitored home-based IADL assessment and data collection paradigm to (a) identify and monitor

TABLE 1 Sample demographics.

	Whole sample ($N = 104$)	CN ($N = 59$)	MCI ($N = 45$)	t or χ^2
Age	74.59 (5.73)	73.64 (5.54)	75.86 (5.81)	1.97^{ns}
Gender (F)	40 (38.5%)	24 (40.7%)	16 (35.6%)	0.283^{ns}
Race (W)	94 (90.4%)	53 (89.8%)	41 (91.1%)	3.85^{ns}
Education	15.65 (2.60)	15.69 (2.42)	15.60 (2.84)	-0.184^{ns}
Employment (E)	82 (78.8%)	13 (22.0%)	5 (11.1%)	2.13^{ns}
SES (NM)	93 (89.4%)	4 (6.8%)	6 (13.5%)	1.35^{ns}
Health history				
Atrial fibrillation	11 (10.6%)	3	8	4.38^{ns}
CHF	1 (0.1%)	1	0	0.78^{ns}
Diabetes	26 (25.0%)	12	14	1.58^{ns}
Hypertension	66 (63.5%)	39	27	0.25^{ns}
High cholesterol	67 (64.4%)	33	34	4.61^{*}
OSA	36 (34.6%)	13	23	9.03^{**}
B-12 deficiency	6 (0.1%)	2	4	1.44^{ns}
Thyroid Dysf.	14 (13.5%)	9	5	0.25^{ns}

Abbreviations: CHF, congestive heart failure; CN, cognitively normal; Dysf., dysfunction; E, employed; F, female; MCI, mild cognitive impairment; NM, needs met but no luxuries; ns, not significant; OSA, obstructive sleep apnea; SES, socioeconomic status; W, non-Hispanic White.

progression of IADL changes that reflect an underlying cognitive decline in older adults at risk for AD and (b) characterize the longitudinal trajectories of remotely monitored IADL decline for at-risk older adults. The initial 90-day baseline activity monitoring period was used for analyses.

2.3 | Clinical assessment procedures

Demographic and clinical assessment data were collected at baseline and at annual study visits for up to 4 years. At each study visit, research personnel administered a standardized battery of health and function questionnaires and the UDS NACC neuropsychological battery[27] plus additional validated neuropsychological measures as part of the study protocol.[28] The annual neuropsychological examination assessed multiple cognitive domains including attention and processing speed, memory, language, executive functioning, and visuospatial construction. For the current study, baseline clinical assessment data were used for analyses.

2.4 | Neuropsychological domain composite z-scores

Raw scores were first transformed into age-corrected z-scores using (1) NACC UDS norms for tests in the UDS battery[27] and (2) normative data from cognitively normal participants seen in the Layton Alzheimer's Disease Center were used for the CERAD word list and Stroop color word test. Cognitive domain composite methodology was adapted from Dodge et al. (2020) to include all tests in the study neuropsychological battery.[27,29] Six cognitive composites were created – attention, executive functioning, language, memory, and visuospatial – by averaging the *z*-scores of all the tests within each domain. A global cognition composite was created by averaging the *z*-scores of the five cognitive domains. Please see Supplemental Table S1 for tests included in each cognitive domain.

2.5 | In-home daily activity monitoring platform and installation

2.5.1 | Computer use

Worktime (Worktime Corporate) is a PC-compatible computer use monitoring software that was installed on participants' own desktop or laptop computers (http://www.worktime.com). If participants had a computer with a Mac operating system, they were unable to participate in this aspect of the study. If participants did not have access to a computer or laptop, a laptop was provided for them ($n = 7$). Two main computer-use variables were derived from the worktime software: (1) the average number of daily minutes spent on the computer and (2) the average variability (standard deviation) in computer-use duration during the 90-day baseline period. A username/password log-in combination was installed on the participants' computers to ensure that only the participants' computer use was monitored. Advanced Encryption Standard (AES)-encrypted data (FIPS 140-2 compliant) was transmitted to ORCATECH servers via Transmission Control Protocol (TCP) connection. Computer-use data were available for 69 participants.

2.5.2 | Pillbox use

Each participant was given a 7-day instrumented pillbox (TimerCap iSort; www.timercap.com) and was instructed to use the pillbox for daily medications. The pillbox contained one compartment for each day of the week with separate compartments for AM and PM medications. Variables that were evaluated included (1) first time of day the pillbox was opened and (2) variability in the first time of the day (standard deviation) that the pillbox was opened. The pillbox would record timestamps each time the lid was opened and closed. The pillbox transmitted information to a hub computer via Bluetooth Low Energy (BLE). The hub computer (Raspberry Pi 3 Model D) received and transferred the pillbox data via a secure virtual private network (VPN) connection to a secure ORCATECH research server. Medication management data were available for 84 participants.

2.6 | Driving behavior

A small, unobtrusive sensing device was used to monitor driving behavior. The device was plugged into the on-board diagnostics (OBD-II) port of each participants' vehicle. Participants did not interact directly with the driving sensor, and there were no audible alerts or sounds produced by the driving sensor device. Two different sensors were used during this study. At the start of the study, the Automatic Pro sensor (Automatic Labs, San Francisco, CA) was used; however, the company shut down in early 2020. As a result, the study team began using Zubie Fleet Connect devices (Zubie, Bloomington, MN; www.zubie.com), which also were installed on the OBD-II port. These devices are compatible with most vehicles sold in the US beginning with the 1996 model year.

For this reason, the driving sensor aspect of the study was only available to those with vehicles who met this criterion. Only data from the Zubie sensor were utilized in the present project to maximize the sample size. A combination of preprogrammed algorithms from Zubie (eg, highway vs nonhighway driving) and those developed by our study team (eg, day vs nighttime driving) were used to derive and analyze driving metrics for days in which at least one trip occurred.[30] For example, to evaluate day and nighttime drives, the sunrise and sunset times were calculated utilizing the longitude and latitude of the driving trip's beginning and ending locations. The duration of the driving trip that occurred during the day was then divided by the total driving trip duration to calculate the percentage of the trip that occurred during the day. The percentage of each trip that occurred at night was one minus the percentage of the trip that occurred during the day. The device did not collect the names of locations or destinations traveled and did not assess driving safety or ability (eg, adherence to speed limit, accidents/crashes). For certain driving variables, filters developed by a clinical and research consensus panel were applied to remove extreme values. Specifically, driving distance needed to be greater than a third of a kilometer and driving duration needed to be between 90 and 28,800 s. Of the 90 subjects with driving data, three were excluded from analysis based on driving data that did not fall within these parameters. Driving data were available for 87 participants.

2.7 | Statistical analysis

SPSS Version 26 was used to conduct all analyses. Intraindividual standard deviations (iSDs) were calculated across four cognitive domain *z*-scores (attention, executive functioning, language, and memory) using cognitive domain *z*-scores from the Aging Well Study as a measure of cognitive dispersion using a previously established algorithm.[31] The visuospatial domain was not included in the iSD composite given that fewer participants ($n = 68$) completed visuospatial tests, which would have limited the analytic power if this domain had been included. One participant was excluded from the sample given an iSD ≥ 3 standard deviations above the sample mean. Hierarchical linear regression was used to examine whether iSD provided incremental information above and beyond mean cognitive performance. In the hierarchical regression analyses, predictor variables included demographic variables (ie, age, sex, education) and global cognitive performance (Step 1) and iSD (Step 2). Outcome variables were the nine continuous sensor variables that have demonstrated group differences between CN and MCI individuals.[17–21] The Benjamini–Hochberg procedure with the Stats_PADJUST extension for SPSS was utilized to correct for multiple comparisons with a false discovery rate set at 0.10.

3 | RESULTS

Individuals with MCI performed worse across all cognitive domains on the neuropsychological battery. Despite this, cognitive composites for all domains were still within the average to low average range for the MCI group.[32] Individuals with MCI demonstrated greater dispersion than those who were CN. Please see Table 2 for baseline neuropsychological and self-report mood measures. Descriptive statistics for all sensor variables are available in Table 3. Correlations between global cognition, iSD, and all sensor variables can be found in Supplemental Tables S2 to S4. Better mean global cognitive performance was associated with longer computer use duration ($R^2 = 0.140$, $\beta = 0.390$, $t = 3.13$, adjusted $p = 0.027$), greater computer-use duration variability ($R^2 = 0.138$, $\beta = 0.336$, $t = 2.65$, adjusted $p = 0.043$), and less distance driven per day ($R^2 = 0.157$, $\beta = -0.280$, $t = -2.49$, adjusted $p = 0.043$). Global cognitive performance was not significantly associated with any other objective daily functioning variables. Including iSD in the model provided incremental information above and beyond mean cognitive performance for two of the three objective daily functioning variables. Specifically, greater dispersion was associated with shorter computer use duration ($R^2\ \Delta = 0.100$, $\beta = -0.321$, adjusted $p = 0.039$) and less computer use variability ($R^2\ \Delta = 0.089$, $\beta = -0.302$, adjusted $p = 0.039$). Additionally, iSD predicted one driving variable that was not significantly associated with mean cognitive performance. Greater cognitive dispersion was associated with shorter average duration of nighttime

TABLE 2 Baseline cognitive and self-report emotional measure characteristics.

	Whole sample ($N = 104$)	CN ($N = 59$)	MCI ($N = 45$)	t
Memory composite	−0.300 (0.64)	0.062 (0.47)	−0.769 (0.51)	−8.54***
Language composite	−0.175 (0.63)	0.102 (0.49)	−0.537 (0.61)	−5.96***
Attention composite	0.009 (0.71)	0.231 (0.59)	−0.283 (0.77)	−3.88***
Executive composite	−0.101 (0.71)	0.198 (0.64)	−0.101 (0.71)	−5.61***
Visuospatial composite	−0.203 (0.71)	−0.059 (0.67)	−0.572 (0.68)	−2.82**
Global composite	−0.166 (0.48)	0.115 (0.35)	−0.534 (0.38)	−9.12***
iSD	0.487	0.434	0.558	2.63**
GDS	1.29 (1.72)	1.07 (1.35)	1.58 (2.08)	1.51^{ns}
GAD-7	1.55 (1.84)	1.49 (1.63)	1.62 (2.10)	0.357^{ns}

Abbreviations: GAD-7, generalized anxiety disorder-7 item; xGDS, Geriatric Depression Scale; iSD, intraindividual standard deviation.
**$p < 0.01$
***$p < 0.001$.

TABLE 3 Baseline sensor variable descriptives.

IADL domain	Sensor variable	Whole sample mean (SD)	CN mean (SD)	MCI mean (SD)	t	P value	No. days monitored mean (SD)
Computer use	Computer-use duration (h)	5.93 (4.43)	6.99 (5.14)	4.60 (2.90)	−2.49	0.008	
	Computer-use duration variability (h)	6.02 (6.61)	7.51 (7.31)	4.26 (5.25)	−2.16	0.017	84 (12)
Pillbox use	Mean time of first pillbox opening	10:32 (4.10)	10:31 AM (4.59)	10:32 AM (3.25)	0.01	0.498	
	Variability in time of first pillbox opening	2.77 (1.33)	2.62 (1.38)	3.01 (1.22)	1.44	0.077	88 (6)
Driving	Median distance driven per day (miles)	19.12 (11.48)	17.09 (10.53)	22.09 (12.30)	1.96	0.027	
	Day-to-day variability in distance driven (miles)	31.06 (27.98)	28.88 (28.04)	34.25 (27.97)	0.87	0.192	
	Mean duration driven on a highway (h)	0.36 (0.32)	0.30 (0.29)	0.44 (0.36)	1.81	0.038	89 (8)
	Mean duration driven during the day (h)	1.01 (0.40)	0.92 (0.35)	1.16 (0.43)	2.75	0.004	
	Duration driven at night (h)	0.17 (0.23)	0.02 (0.09)	0.04 (0.11)	1.92	0.030	

Abbreviations: CN, cognitively normal; MCI, mild cognitive impairment; SD, standard deviation.

driving ($R^2 = 0.122$, $R^2\ \Delta = 0.072$, $\beta = -0.272$, adjusted $p = 0.039$). Regression analysis results for all variables can be found in Table 4.

4 | DISCUSSION

This study evaluated whether cognition on traditional neuropsychological assessment was associated with passively assessed IADLs that spanned three domains: computer use, pillbox use, and driving. To our knowledge, this is the first study to examine relationships between cognitive dispersion and objectively measured activities of daily living using unobtrusive sensor technologies. There were two main findings: (1) global cognitive performance demonstrated associations with four out of nine passively assessed IADLs and (2) cognitive dispersion provided incremental information in the prediction of objective passively assessed daily activities above and beyond mean global cognitive performance in three of the four passively assessed IADLs for which global cognition was also a significant predictor.

Consistent with prior studies, individuals classified as having MCI exhibited greater levels of cognitive dispersion compared to CN older adults.[6–11] This further supports the idea that dispersion may increase with disease progression and serve as a prodromal indicator of cognitive change.[10,11–12] Additionally, our findings were generally consistent with prior work that found group differences between CN older adults and those with MCI on six of the nine passively assessed IADLs.[16–21] A lack of group differences seen in prior work for pillbox use variables and day-to-day variability in distance driven may be related to various factors, including cohort differences, different driving sensors being used, and a change in daily activity patterns due to the COVID-19 pandemic, which led to older adults spending more time at home, having more structured daily routines, and traveling less during lockdown periods.[33,34]

TABLE 4 Hierarchical regression analyses examining relationships between cognitive dispersion and passive sensing variables when controlling for demographics and mean global cognitive performance.

	R^2	*F* change	Significant *F* change/ unadjusted *p* values	Standardized beta coefficient	Benjamini-Hochberg corrected *p* value
Computer-use duration (h)					
Step 1	0.140	$F(4.66) = 2.684$	0.039		
Step 2	0.240	$F(1.65) = 8.582$	0.005	−0.321	0.039
Computer-use duration variability (h)					
Step 1	0.138	$F(4.64) = 2.553$	0.047		
Step 2	0.227	$F(1.63) = 7.239$	0.009	−0.302	0.039
Mean time of first pillbox opening					
Step 1	0.017	$F(4.87) = 0.385$	0.819		
Step 2	0.028	$F(1.86) = 0.977$	0.326	0.107	0.734
Variability in time of first pillbox opening					
Step 1	0.098	$F(4.87) = 2.357$	0.060		
Step 2	0.098	$F(1.86) = 0.002$	0.963	−0.005	0.963
Median distance driven per day (miles)					
Step 1	0.157	$F(4.80) = 3.725$	0.008		
Step 2	0.163	$F(1.79) = 0.568$	0.453	0.079	0.815
Day-to-day variability in distance driven (miles)					
Step 1	0.036	$F(4.80) = 0.750$	0.561		
Step 2	0.036	$F(1.79) = 0.006$	0.937	−0.009	0.963
Mean duration driven on a highway (h)					
Step 1	0.106	$F(4.80) = 2.376$	0.059		
Step 2	0.107	$F(1.79) = 0.037$	0.848	0.021	0.963
Mean duration driven during the day (h)					
Step 1	0.144	$F(4.80) = 3.364$	0.013		
Step 2	0.145	$F(1.79) = 0.051$	0.822	−0.024	0.963
Duration driven at nighttime (h)					
Step 1	0.050	$F(4.80) = 0.387$	0.387		
Step 2	0.122	$F(1.49) = 6.500$	0.013	−0.272	0.039

Note: Step 1: age, sex, education, and mean global cognitive performance; Step 2: iSD.

Our results demonstrate that global cognitive performance is associated with some aspects of objectively assessed daily functioning, including computer-use duration, computer-use duration variability, and total distance driven. This is notable as a recent meta-analysis suggested that there are often weak and variable relationships observed between cognition and self-reported daily functioning deficits in those with MCI.[35] It is likely that using objective methods such as passive monitoring may result in stronger and more stable associations across studies.[2] Results examining the relationship between computer use and global cognitive performance are partially aligned with prior work which also indicated that less computer-use time is associated with smaller hippocampal volume and increased likelihood of having MCI.[36,37] As suggested by Kaye and colleagues (2014), older adults with cognitive impairment may find it increasingly difficult to navigate technology, which frequently changes and becomes more complex, leading to less use over time.[17] In contrast with Kaye et al. (2014), better cognition was associated with less variability in computer duration in our study. One potential explanation for reduced variability in computer time among those with poorer cognition is that individuals with cognitive impairment have more structured daily routines, which may reduce variability.[21] Additionally, in a prior study CN older adults were observed to use a wider variety of computer applications (eg, word processing software, email, Internet), which may contribute to increased variability in computer-use duration compared to those with MCI who engage in a restricted range of computer-related activities.[21] Regarding driving, better global cognitive performance was associated with less time driven.

Lastly, no association between objective pillbox variables and cognitive performance was seen in this study despite prior findings demonstrating that MCI individuals often open their pillbox later in

the day and have a more variable daily first time of pillbox opening compared to CN older adults.[19] Prior work demonstrated that among those with executive dysfunction, the complexity of daily life routines interacts with cognition to predict medication management in older adults.[38] Therefore, a shift toward more structured and simpler routines with reduced executive demands during the COVID-19 pandemic may have reduced group differences in these metrics and contributed to divergent findings.

Our findings also demonstrated that cognitive dispersion explained additional variance in the association between cognitive and both passively assessed computer-use variables above and beyond mean global cognitive performance. Specifically, greater dispersion was associated with shorter computer-use duration times and less variability in computer-use duration, as expected. These findings mirror the aforementioned prior study suggesting that cognitive impairment was associated with less computer-use duration and greater variability in computer-use duration. Dispersion was also independently associated with duration of nighttime driving such that greater dispersion was associated with less time spent driving at night. This finding aligns with multiple studies demonstrating that older adults with cognitive impairment engage in compensatory behaviors to reduce their driving risk such as reducing nighttime driving.[39,40] These findings contribute to the notion that cognitive dispersion has the potential to improve the detection of early cognitive and functional changes, especially when more intrusive or costly procedures, like imaging or CSF analysis, are not possible. Additionally, these observed patterns provide real-world support through the use of objective IADL assessment methods for the findings of Bangen et al. (2019), which revealed that dispersion was associated with informant-reported functional decline among older adults with and without MCI.[7] Given the small sample sizes, we were unable to test whether dispersion may interact with cognitive status group to predict functional status. However, it is likely cognitive dispersion's predictive capability may be strongest in those in subjective cognitive decline and MCI but may wane when assessing functional decline in individuals at either end of the cognitive spectrum (ie, cognitively intact individuals at low risk for AD/ADRD and individuals with dementia).[7]

4.1 | Limitations and future directions

Despite this study's many strengths, it is not without limitations. This cross-sectional sample was small and homogeneous with respect to race, education, and socioeconomic status. The small sample size impacted the ability to evaluate the predictive utility of iSD by cognitive subgroup (ie, CN vs MCI). Further work is needed on larger and more diverse samples to validate and expand upon these preliminary insights cross-culturally, across diagnoses, and longitudinally. The impact of the COVID-19 pandemic is an important consideration for the present analysis as it impacted participants' activity patterns, as previously demonstrated by our group and others.[33,34] A final limitation was technological complications, including needing to change the driving sensor suppliers, wireless connection problems, and sensor incompatibility with some cars and computer operating systems, which led to the inability to capture data from some participants. Future studies may wish to explore relationships between cognitive dispersion and composites of passively assessed IADL functioning to better understand these cross-sectional and longitudinal relationships. Upcoming work will utilize data reduction techniques to identify which sensor variables are the most predictive of cognitive status to create an objectively assessed IADL functioning composite, which may enhance diagnostic precision and prediction of disease progression.

5 | CONCLUSIONS

Our results were generally consistent with an emerging body of literature, which suggests that cognitive dispersion may be useful in understanding cognitive and functional trajectories in the aging population. Specifically, cognitive dispersion provided incremental information in the prediction of passively assessed computer use and driving abilities. These insights emphasize the potential benefit of incorporating measures of dispersion for a more holistic understanding of the relationship between cognition and objectively assessed IADLs. The importance of understanding cognitive and functional changes has grown as the demographic landscape shifts toward an older population.

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CONFLICTS OF INTEREST STATEEMNT

The authors have no conflicts of interest to disclose. Author disclosures are available in the supporting information.

CONSENT STATEMENT

All human subject participants provided informed consent.

ORCID

Alyssa N. De Vito https://orcid.org/0000-0002-4078-3869

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SUPPORTING INFORMATION

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

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