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Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring 1 (2015) 472-480

Alzheimer's & Dementia

Cognitive & Behavioral Assessment

Computer mouse movement patterns: A potential marker of mild cognitive impairment

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Abstract

Introduction: Subtle changes in cognitively demanding activities occur in mild cognitive impairment (MCI) but are difficult to assess with conventional methods. In an exploratory study, we examined whether patterns of computer mouse movements obtained from routine home computer use discriminated between older adults with and without MCI.

Methods: Participants were 42 cognitively intact and 20 older adults with MCI enrolled in a longitudinal study of in-home monitoring technologies. Mouse pointer movement variables were computed during one week of routine home computer use using algorithms that identified and characterized mouse movements within each computer use session.

Results: MCI was associated with making significantly fewer total mouse moves ($P < .01$) and making mouse movements that were more variable, less efficient, and with longer pauses between movements ($P < .05$). Mouse movement measures were significantly associated with several cognitive domains (P values $<.01–.05$).

Discussion: Remotely monitored computer mouse movement patterns are a potential early marker of real-world cognitive changes in MCI.

Keywords: Everyday functioning; Cognitive assessment; Technology; Ecological validity; Instrumental activities of daily living; Aging; Computer use; Early detection of cognitive decline; Mild cognitive impairment; Functional assessment; Remote monitoring

1. Introduction

Alzheimer's disease (AD) is a leading cause of death in America [1], and currently there is no prevention or cure. An important goal is to identify presymptomatic changes in healthy community-dwelling individuals that are predictive of future cognitive decline and transition to mild cognitive impairment (MCI) and AD. Reliable detection and tracking of early cognitive changes will be critical for deriving maximum benefits from currently available treatments, measuring response to preventative and symptomatic treatments in clinical trials, and facilitating cost-effective, large scale community cognitive screening [2–4].

To identify meaningful cognitive changes in community-dwelling older adults as early as possible, practical assessment tools are needed that are cost-effective, noninvasive, and nontaxing. Assessing β-amyloid and tau biomarkers is costly and difficult to apply widely among presymptomatic older adults, and reduction of β-amyloid

The authors have no potential conflict of interest with this work.

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http://dx.doi.org/10.1016/j.dadm.2015.09.006

in the brain has not yet demonstrated clear clinical benefits [5]. Conventional standardized cognitive tests have been shown to be strong early predictors of transition to future dementia [6–10]. However, conventional cognitive tests are typically administered infrequently and are not ideally suited to tracking intraindividual cognitive change. These tests are often used to make inferences about an individual's ability to function in the real world, and yet due to fundamental differences between the testing (clinic) setting and one's real-world environment, the generalizability or ecological validity of these tests has been questioned [11].

Measuring daily function in aging, MCI, and dementia populations has its own unique challenges. For example, there is large individual variability in what activities are typically performed by older adults and how they are carried out (e.g., medication management, finances, appointments, computer use, shopping, and household tasks). In addition, functional assessment instruments that do not discriminate with fine precision across the normal to mildly impaired range of functional ability can lead to ceiling effects for people with very early MCI [2]. There are data to indicate, for example, that subtle but consistent changes signaling less efficient or effective performance in carrying out everyday activities occur in early MCI and are directly associated with cognitive changes [12–14]. These very early and gradual changes may be important signals of incipient neurodegenerative disease but they are not well captured by available functional assessment measures that are largely based on self- or informant-report. There is a need for reliable and valid instruments that are able to measure subtle cognitive changes as they develop in presymptomatic and MCI older adults' daily lives with greater individualization and precision [15].

Recent advances in wireless technology, pervasive computing, and multidomain analytics have made it possible to unobtrusively measure cognitive activity in an individual's own environment, every time a person interacts with common devices such as a computer, automobile, telephone, or pillbox [16–19]. Continuous (e.g., daily, weekly, monthly) assessment of individuals' day-to-day functioning makes it possible to more accurately track and measure relevant intraindividual changes in daily functioning that emerge earlier than with conventional yearly cognitive or functional assessment methods alone. Applied to clinical trials, frequently measured unobtrusive activity data would require smaller sample sizes to obtain sufficient power for detecting meaningful change, facilitating faster and more productive trials and drug development [20]. Another advantage of this new assessment paradigm is that monitoring technology is discretely embedded within commonly used devices and requires no extra effort or action by the individual outside of their normal routine [21]. Thus, the information obtained is representative of individuals' actual daily functioning under normal conditions. Given that the fastest growing segment of the population adopting mobile and computer technology are those older than age 65, it is now feasible and relevant to monitor cognitive functioning of older adults through computer use.

The present study is part of a larger, longitudinal cohort study. In the study reported here, we were interested in learning whether ambiently assessed computer mouse movement patterns taken from 1 week of routine home computer use would discriminate between older adults with and without MCI. Owing to their mild cognitive deficits and relative difficulty managing complex everyday technology including computer use [16,22], we hypothesized that the mouse movement patterns of older adults with MCI would be less efficient compared with those of the cognitively intact group. In addition, we examined relationships between the mouse movement measures and traditional cognitive assessment measures in the total sample, regardless of diagnosis, to provide preliminary evidence of convergent validity of these new measures across the spectrum from normal cognition to MCI.

2. Methods

2.1. Study design

All participants provided written informed consent and were already enrolled in one of two ongoing studies of in-home monitoring: the ORCATECH Life Laboratory study and the Intelligent Systems for Assessing Aging Changes (ISAAC) study (www.orcatech.org). Participants were recruited from the Portland, OR, USA, metropolitan area through advertisement and presentations at local retirement communities. The study protocols were approved by the Oregon Health & Science University Institutional Review Board (Life Laboratory IRB #2765; ISAAC IRB #2353). Both studies use the same in-home sensor technology and computers to detect early behavioral and cognitive changes that occur with aging. Additional details of the sensor systems and study protocols have been published elsewhere [21,23]. Inclusion criteria were $\geq$60 years for the Living Laboratory study and $\geq$80 years for the ISAAC study, living independently (living with a companion or spouse was allowed, but not as caregiver), not demented as evidenced by a mini-mental state examination (MMSE) [24] score $>$24, a clinical dementia rating (CDR) [25] scale score $\leq$0.5, and in average health for age. Exclusionary criteria included chronic or poorly controlled medical illnesses. A total of 265 participants were enrolled beginning in 2007. The participants lived in a variety of settings—from apartments in organized retirement communities to free-standing single-family homes.

2.2. Study participants

There were 125 active Life Laboratory/ISAAC participants during 2011–2012. Of this group, there were 83 who

were "computer users" and 62 with adequate mouse movement data recorded. For the present study, we report data for the 62 participants who were from single-person homes or were the only computer user at home and who had available mouse movement data from a 1-week period close to their 2011–2012 annual clinical evaluation. Participants used desktop computers with standard mice and high-speed Internet access that they had in their homes as part of their participation in ORCATECH research.

2.3. Procedures and assessments

Participants received clinical assessments during annual visits in their home using a standardized battery of tests including the MMSE [24], the geriatric depression scale [26], and functional activities questionnaire [27]. Health status was further assessed by the modified cumulative illness rating scale [28]. Participants also completed a brief weekly online health survey, in which they reported their current activity, health, and mood (e.g., feeling down or blue in the past week: yes/no), along with any changes in the past week.

Diagnosis of MCI was consistent with the criteria defined by Jak et al. [29] and with the criteria outlined by the National Institute on Aging-Alzheimer's Association workgroup [30] (Table 1). The Jak [29] criteria for classifying MCI have been shown to better characterize cognitive subtypes, associate with AD biomarkers, show stability of diagnosis over time, and identify more patients who actually progress to dementia than other diagnostic methods [8]. Diagnosis of MCI or normal cognition was made at each participant's annual clinical evaluation that occurred in the year in which we obtained the mouse movement data.

Neuropsychological tests used for assessment of MCI are presented in Table 2. Cognitive domain z-scores were calculated using group mean and standard deviations of the raw test scores from all cognitively intact subjects (CDR = 0) at study entry into the ORCATECH cohort (n = 180). Global cognition z-scores were tabulated from these cognitive tests in the domains of working memory, attention and processing speed, memory, executive function, and visual perception/construction. The participants in the present study are part of the original normative cohort.

2.4. Development of objective computer mouse movement measures

By definition, the mouse pointer is the arrow that moves on the screen when the mouse is moved. The continuous stream of raw mouse pointer data obtained over the 1-week study period were first divided into discrete computer use sessions for each participant. A session was defined to begin when a participant logged into the computer and to end when computer activity had ended for a sufficiently long period and there was no new activity before a subsequent login. The mouse pointer data stream for a particular computer session were a single trajectory of position and time data that have been unevenly sampled in time. An algorithm was applied to that data to divide the mouse pointer data stream into a sequence of individual movements made purposefully by the participant [31,32].

Table 1
Criteria for MCI classification

1. Objective evidence of impairment on at least two neuropsychological tests within one or more of six cognitive domains, with scores falling at least one standard deviation or more below the mean values stratified by age based on available normative data
2. Nonfulfillment of criteria for dementia
3. Preserved general cognitive functions as confirmed by a score of ≥24 on the MMSE
4. No significant impact on functional abilities, as confirmed by two or fewer activities marked as dependent on the FAQ
5. Absence of severe depression as confirmed by a score <5 on the 15-item GDS.

Abbreviations: MCI, mild cognitive impairment; MMSE, mini-mental state examination; FAQ, functional activities questionnaire; GDS, geriatric depression scale.

NOTE. Diagnosis of MCI was consistent with the criteria defined by Jak et al. [29] and with the criteria outlined by the National Institute on Aging-Alzheimer's Association workgroup [30].

Table 2
Neuropsychological tests used for MCI classification

Cognitive domain	Neuropsychological tests
Memory	WMS-R Logical Memory II Story A [33]
	WMS-R Visual Reproduction II [33]
	CERAD Word-List Recall [34]
Language	Boston Naming Test [35]
	Category fluency (animals) [36]
Executive function	Letter fluency (CFL) [37]
	Trail Making Test Part B [38]
	Stroop color-word conflict [39]
Processing speed	WAIS-R Digit Symbol [40]
	Trail Making Test Part A [38]
	Stroop color naming [39]
Working memory	WAIS-R Digits Backward [40]
	WAIS-III Letter Number Sequencing or WAIS-IV Digit Sequencing [41]
	MMSE item WORLD backward [24]
Visual perception/ Construction	WAIS-R Block Design [40]
	WAIS-R Picture Completion [40]
	WMS-R Visual Reproduction I [33]

Abbreviations: MCI, mild cognitive impairment; WMS-R, Wechsler memory scale-revised; CERAD, consortium to establish a registry for Alzheimer's disease; WAIS-R, Wechsler adult intelligence scale-revised; WAIS-III, Wechsler adult intelligence scale-third edition; MMSE, mini-mental state examination.

More specifically, for each computer use session, a stream of position and time data (x,y;t) for the pointer on the screen were obtained for each participant. When the computer session was started, the initial position of the mouse pointer and the time were recorded. Subsequent positions and times were recorded whenever the pointer's position exceeded a distance of five pixels from the last recorded position using a Manhattan distance metric. Once the algorithm divided the data stream into movements, it was possible to analyze the identified mouse movements in greater detail, and also to look at the lengths in time intermove intervals that lie between two adjacent mouse movements. The algorithm was applied to the data that identified individual pointer movements for each participant within each computer use session [31]. In a previous study, the algorithm had been shown to identify mouse movements with physically reasonable characteristics and that these movements could be used to construct an estimator for subject performance on the trail making test (TMT) [31,32]; the estimator of TMT performance using mouse movements was a somewhat simplified version of an estimator for participant performance on TMT constructed using a computer game, and which included measurements based on mouse movements in a more detailed model [42].

For each pointer movement, various measures were computed. It is important at this point, to make the measures clear, to provide a simplified model of how a computer processes movements of the mouse. The mouse moves on the table-top in a two-dimensional physical space of positions on the table-top; these positions may be thought of as measured in conventional units (e.g., centimeter) in some coordinate system on the table-top. The computer translates positions on the table-top into an internal representation of positions of the mouse as positions in an abstract and discrete coordinate system as measured in an abstract system of units—counts. The computer then takes positions of the mouse in this abstract coordinate system and translates them into positions of the pointer on the computer screen measured in pixels in some coordinate system on the screen. We recorded mouse position data using the computer's internal representation of the mouse position in counts, thus movements are characterized as changes in position with distances measured in counts. The objective mouse movement variables we examined for this study are summarized measures from each mouse movement recorded during the 1-week period. The measures include straight-line ("as the crow flies") distance between starting and end points of the movement, in counts (delta); total distance actually traveled by the mouse in counts (D, the distance D cannot be less than the distance delta and is generally somewhat longer as participants generally do not move the mouse along a perfectly straight line); time taken to make a mouse movement in milliseconds (T); mouse movement curvature (K) where K = delta/D, and time spent idling or pausing between successive mouse movements in milliseconds (idle). A typical mouse movement can be depicted graphically like an arc, "(" where the total distance (D) is the arc, the net distance (Delta) connects the end points of the arc, and the curvature of the arc is (K); we note that K ranges from 0 to 1 where 0 indicates a movement that is a loop and 1 indicates a movement along a straight line (Fig. 1). Statistics based on Gaussian models provided a poor description of the distributions of the measures and we adopted a more robust approach using the median and interquartile range (IQR) to characterize the measures. The median of each measure was taken for the week, together with the IQR to assess variability. Thus, for each objective mouse movement measure, we obtained summaries of central tendency and variability for the 1-week study period.

2.5. Statistical analysis

Cross-sectional group comparisons of demographic, clinical variables, and objective mouse movement variables were made first using unadjusted Student *t* test or Wilcoxon ranked-sum test for continuous variables and the Pearson χ^2 test for categorical variables at participants' 2011–2012 annual clinical evaluation. Multiple regression models were then generated with the objective mouse movement variables as unique outcomes, adjusted for age and education because age and association can be associated with cognitive status. Spearman ρ correlations were run to examine relationships between the

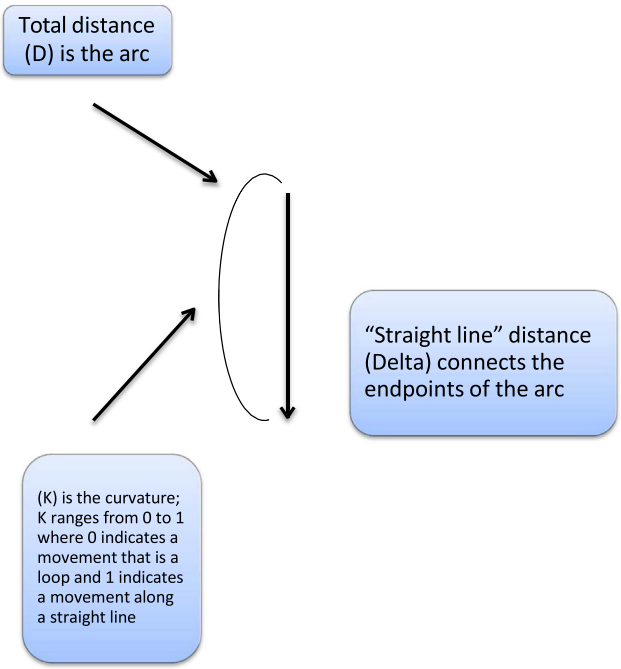

Fig. 1. Graphical representation of a mouse movement.

objective mouse movement variables and the cognitive test domains in the total sample regardless of diagnosis. Analyses were performed using SAS software 9.3 (Cary, NC, USA).

3. Results

3.1. Demographic, clinical, and objective mouse movement variables

Table 3 presents the demographic, clinical, and objective mouse movement variables for the study sample. MCI participants had lower scores than the cognitively intact group on the MMSE and were less educated than cognitively intact older adults ($P < .05$). There were no significant group differences in reported depressed mood in the past month. Over the 1-week study period, the MCI group's mouse movements were shorter in distance (delta, D) compared with those of the cognitively intact group ($P < .05$; Fig. 2). The MCI group also took less time to make individual mouse movements (T; $P < .05$). The MCI group generated a larger and more variable number of more curved or looped mouse movements (IQR_K; $P < .05$), consistent with a less direct and less efficient approach to reach an icon. The MCI group demonstrated a larger and more variable length of pauses between mouse movements (IQR_Idle; $P < .05$), consistent with the MCI group taking longer to make the next movement after the last movement was made. The MCI group (mean = 1497) contributed significantly fewer total mouse moves to this analysis than did the cognitively intact group (mean = 9679; $P < .01$). The cognitively intact group (mean = 9.5) contributed almost twice as many total computer sessions during the week of interest than the MCI group ($M = 4.9$), although this difference was not statistically significant.

Table 3
Demographics and mouse movement variables

Demographics and variables	Cognitively intact, mean (SD), n = 42	MCI, mean (SD), n = 20
Age (y)	87.9 (5.2)	87.5 (6.6)
Gender (% Women)	88	80
Education (y)	15.6 (2.5)	13.5 (2.9)**
Any depressed (down/blue) mood (% past month from weekly health survey)	5	5
MMSE	28.8 (1.2)	27.3 (1.4)**
CIRS	20.0 (2.1)	20.6 (2.6)
Median delta	50.6 (23.0)	36.5 (14.6)*
IQR delta	138.2 (50.5)	112.0 (50.4)
Median D	56.5 (24.6)	42.3 (19.3)*
IQR D	150.5 (54.7)	123.7 (55.9)
Median T	237.2 (72.2)	199.9 (55.5)*
IQR T	332.6 (122.2)	325.7 (143.7)
Median K	0.88 (0.02)	0.87 (0.03)
IQR K	0.14 (0.02)	0.15 (0.02)*
Median idle	308.7 (61.4)	346.6 (104.6)
IQR idle	832.0 (424.6)	1249.9 (942.6)*
Number of mouse movements contributed	7871 (9679)	1497 (1684)**
Number of computer sessions contributed	9.5 (11.2)	4.9 (4.2)

Abbreviations: SD, standard deviation; MCI, mild cognitive impairment; MMSE, mini-mental state examination; CIRS, cumulative illness rating scale; Delta, straight-line distance traveled by the mouse, between starting and end points, in counts; IQR, interquartile range; D, total distance traveled by the mouse in counts; T, time taken to make a mouse movement in milliseconds; K, mouse movement curvature, ranging from 0 to 1 (0 = looped, 1 = straight line); idle, time spent idling or pausing between successive mouse movements in milliseconds.

NOTE. *$P < .05$; **$P < .01$.

3.2. Predictive ability of the mouse movement measures

Multiple regression analyses showed that after adjusting for covariates (age and education), MCI was predictive of generating a larger and more variable number of more curved or looped mouse movements (IQR_K; $P = .008$). MCI was also predictive of generating larger and more variable pause lengths between successive mouse movements (IQR_Idle; $P = .04$; Table 4). The other mouse movement variables significant in Table 3 (median delta, median D, and median T) did not remain significant after adjusting for age and education.

3.3. Correlational analyses between mouse movement and cognitive measures

In Spearman ρ correlational analyses with all 62 participants, the objective mouse movement measures were significantly positively associated with conventional neuropsychological tests in the cognitive domains of executive functioning, attention, visual-spatial, and global cognition in the total sample (P values <.01–.05; Table 5; Fig. 3). Given that we defined our groups using comprehensive neuropsychological criteria, we used the entire sample to explore relationships between the mouse movement

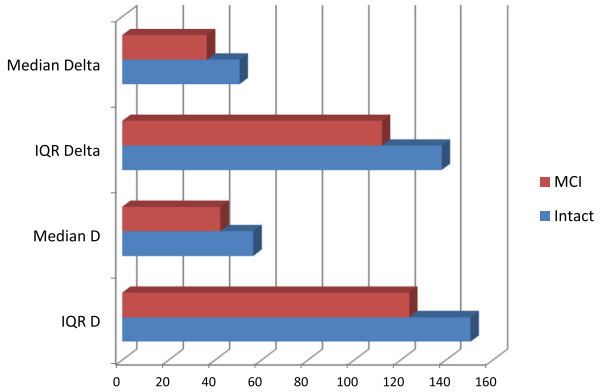

Fig. 2. Mouse movement variables by cognitive status. Mouse position data were recorded using the computer's internal representation of the mouse position in counts, thus mouse movements are characterized as changes in position with distances measured in counts. Abbreviations: IQR, interquartile range; MCI, mild cognitive impairment.

Table 4
Associations between cognitive status and mouse movement variability derived from one week of data

	Outcome, movement curvature (IQR_K)		Outcome, time spent idling (IQR_Idle)	
Covariate	Coefficient	*P* value	Coefficient	*P* value
MCI (reference: cognitively intact group)	0.013	.008**	386.8	.04*
Age (y)	−0.001	.03*	−15.0	.31
Education (y)	0.002	.05	−12.4	.70

Abbreviations: IQR, interquartile range; MCI, mild cognitive impairment.
NOTE. *$P < .05$, **$P < .01$.

measures and cognitive test domains to avoid circularity in the results.

4. Discussion

In this exploratory study, we examined whether ambiently assessed computer mouse movement patterns taken from 1 week of routine home computer use would discriminate between older adults with and without MCI. Compared with cognitively intact older adults, older adults with MCI generated fewer total mouse moves and made a larger and more variable number of more curved or looped mouse movements, consistent with a less direct and less efficient approach to reach an icon on the screen. Older adults with MCI also demonstrated greater variability in the length of pauses made between successive mouse movements, suggesting that older adults with MCI were less consistent in the time they took to make the next movement after the last movement was made. One interpretation of these data is that the mouse movement patterns of older adults with MCI are less efficient and less accurate than cognitively normal older adults. Consistent with prior findings that older adults with MCI have more difficulty using everyday technologies [16,22], an explanation is that due to their mild cognitive deficits, older adults with MCI had relative difficulty and were slower to use a mouse to effectively navigate a computer interface.

Across the spectrum of healthy aging to MCI, we found significant positive correlations between the objective mouse movement measures and cognitive domain z-scores derived from conventional cognitive tests. Global cognition, executive functioning, attention, and visual-spatial abilities were the cognitive domains most strongly associated with the objective mouse measures. These results provide preliminary evidence that the ways in which older adults use their computer mouse when engaging in routine computer tasks are related to established cognitive constructs and support the interpretation that differences observed in the objective mouse movement measures between older adults with and without MCI are related to mild cognitive deficits.

In earlier ORCATECH studies of home computer use, we showed that over time, older adults with MCI spend less time on their home computer and have more inconsistent usage patterns [16]. More recently, we found that on specific routine computer tasks, such as filling out an online questionnaire, older adults with MCI are slower, need more assistance, and put it off to later in the day [12]. In other functional domains, we have shown that the ability to adhere to a medication regimen [17], the number of incoming phone calls [18], and proportion of words spoken in conversation [13,43] are all sensitive to mild cognitive changes associated with MCI in older adults. Daily computer use in older adults without dementia has also been shown to be related to brain regions linked to memory function and the processing of visual and spatial stimuli, areas previously shown to be associated with conversion to Alzheimer's dementia [44]. Data from the present study are consistent with these previous studies and add to our growing evidence base that routine daily activities in the home can be remotely monitored to detect subtle cognitive deficits in older adults [12,13,16,17,21].

Table 5
Spearman's ρ-positive correlations between mouse movement variables and cognitive domain z-scores among 62 older adults

	Cognitive domains					
Computer use measures	Global cognition	Executive functioning	Working memory	Attention	Memory	Visual spatial
Median delta	$P < .01$	$P < .01$	NS	$P < .05$	NS	$P < .01$
IQR delta	$P < .01$	$P < .01$	NS	NS	NS	$P < .01$
Median D	$P < .01$	$P < .01$	NS	$P < .05$	NS	$P < .01$
IQR D	$P < .01$	$P < .01$	NS	$P < .05$	NS	$P < .01$
Median T	$P < .01$	$P < .01$	NS	$P < .05$	NS	$P < .01$
IQR T	NS	NS	NS	NS	NS	$P < .05$
Median K	NS	NS	NS	NS	NS	$P < .01$
IQR K	NS	NS	NS	NS	NS	NS
Median idle	NS	NS	NS	NS	NS	NS
IQR idle	NS	NS	NS	NS	NS	NS

Abbreviations: NS, correlations that were not statistically significant; IQR, interquartile range; delta, straight-line distance traveled by the mouse, between starting and end points, in counts; D, total distance traveled by the mouse in counts; T, time taken to make a mouse movement in milliseconds; K, mouse movement curvature, ranging from 0 to 1 (0 = looped, 1 = straight line); idle, time spent idling or pausing between successive mouse movements in milliseconds.
NOTE. Individual participant neuropsychological test scores were z-normalized, summed, and averaged for each cognitive domain. Cognitive domain z-scores were tabulated from 2 to 3 representative neuropsychological tests for each domain.

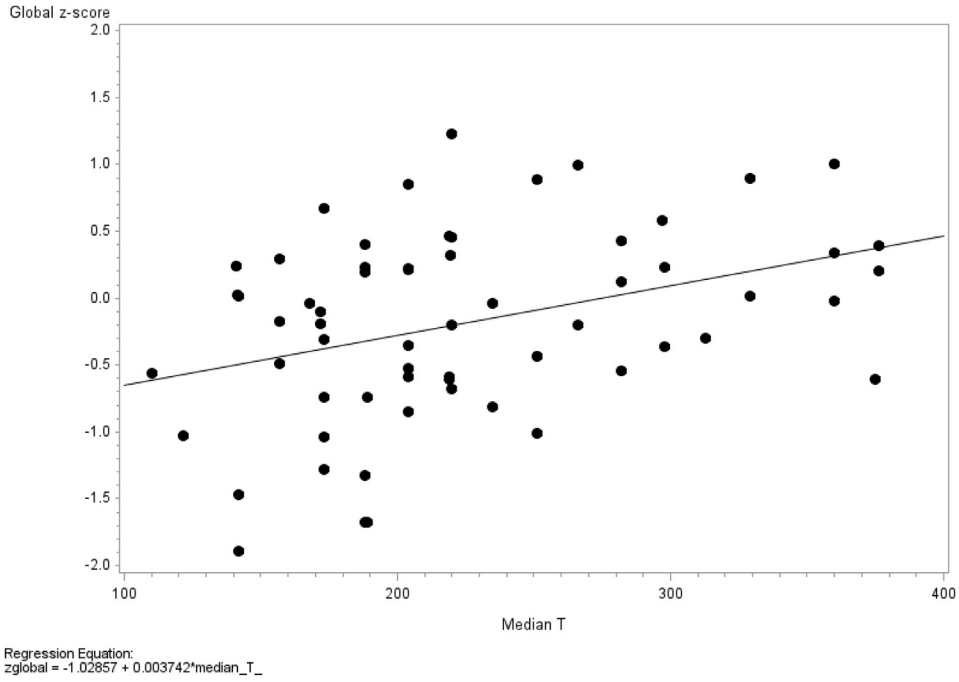

Fig. 3. Scatterplot displaying median time taken to make a mouse movement in milliseconds (T) by global cognitive z-score among 62 older adults. Cognitive domain z-scores were calculated using group mean and standard deviations of the raw test scores from all cognitively intact subjects (CDR = 0) at study entry into the ORCATECH cohort (n = 180). Global cognition z-scores were tabulated from cognitive tests in the domains of working memory, attention and processing speed, memory, executive function, and visual perception/construction. Abbreviations: CDR, clinical dementia rating.

The current conclusions must be interpreted with limitations in mind. The cohort is a relatively homogenous sample of predominately Caucasian (80%), well-educated community-dwelling volunteers living alone (or only computer user in the household) with low levels of depression and few health comorbidities. This may reduce the generalizability of our findings. However, to the degree that these participants represent the growing older adult computer users of the future, the results are promising. Additional studies with larger and more diverse samples sizes of MCI participants over longer periods of time are needed to confirm these findings. Given the exploratory nature of this study and our relatively small sample size, we used a conventional *P* value of .05 when analyzing the data. If we would have used a more stringent multiple comparison adjusted *P* value of .01, IQR-idle (length of pauses between mouse movements) would lose its significant association with cognitive status. Further studies with larger sample sizes are warranted to confirm these preliminary results. We did not classify into MCI subtypes and this could be done in future studies to better characterize how individuals across the spectrum of MCI perform on these mouse movement measures. A general limitation of using continuous, high-frequency behavioral data is that processing, analyzing, and distilling large amounts of data into meaningful measures are time and resource intensive. For example, depending on the programs and computing platforms used, it could take weeks or months to process a large data set and derive meaningful variables of interest. These challenges could be mitigated in the future using more powerful and advanced software and hardware.

Future research will focus on further validation of these and other unobtrusive cognitive assessments embedded within remotely monitored home computer use (e.g., computer keystrokes, eye movement tracking) [45] as well as other everyday activities. In the era of touch screens, tablets, and smart phones, development of objective "touch screen" measures are also warranted for monitoring cognitive and functional change, particularly with the aging of the technologically savvy baby boomer population. Future directions will also include examining the ability of the objective mouse movement measures to assess cognitive status and cognitive change when restricted to a specific computer task in which there is increased control over the computer interface, content, structure and demands (e.g., computer game or online survey). Ultimately, we will use longitudinal data to determine whether these passively assessed computer mouse movement measures can be used to improve the prediction of future cognitive decline (e.g., MCI) in cognitively intact older adults.

Acknowledgments

The authors thank their colleagues, research assistants, technicians, programmers, analysts, and volunteers who invite us into their homes and lives.
This work was supported by the National Institutes of Health grants AG024978, AG024059, AG023477, P30AG008017, and AG042191.

RESEARCH IN CONTEXT

1. Systematic review: The authors reviewed the literature using traditional (e.g., PubMed) sources and meeting abstracts and presentations. There have been several recent publications describing technology-based assessment methods for aging and dementia, and these relevant citations are appropriately cited.
2. Interpretation: Our findings suggest that the mouse movement patterns of mild cognitive impairment (MCI) individuals are less efficient and less accurate than cognitively normal individuals. These findings are consistent with prior studies showing that older adults with MCI have more difficulty using everyday technologies including other aspects of computer use.
3. Future directions: The article contributes to the growing evidence base that cognitively demanding routine daily activities in the home can be monitored to detect MCI. Ultimately, longitudinal data will be used to determine whether objective computer mouse movement measures can be used to improve the prediction of future cognitive decline in cognitively intact individuals and those with MCI.

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