

Evaluating the Accuracy of Online and In-Clinic Subjective Cognitive Decline Assessments in Detecting Cognitive Impairment: Multicohort Study

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Abstract

Background: Scalable tools to efficiently identify individuals likely to have cognitive impairment (CI) are critical in the Alzheimer's disease and related dementias field. The Everyday Cognition scale (ECog) and its short form (ECog12) assess subjective cognitive and functional changes and are useful in predicting CI. Recent advances in online technology have enabled the use of web-based cognitive tests and questionnaires to identify cognitive impairment (CI) with greater convenience and scalability. While the effectiveness of the ECog has been demonstrated in clinical settings, its potential to detect CI in remote, unsupervised formats remains underexplored.

Objective: This study aimed to compare the ability of the online ECog and the in-clinic ECog in distinguishing between individuals with CI and those who are cognitively unimpaired (CU), and to evaluate the effectiveness of the ECog12—the abbreviated version of the ECog—compared to the full-length ECog in an online setting.

Methods: Participants were recruited from the Brain Health Registry (BHR; online) and Alzheimer's Disease Neuroimaging Initiative (ADNI; in-clinic) with available clinical diagnoses. The ability of the self-rated ECog (Self-ECog), study partner-rated ECog (SP-ECog), Self-ECog12, and SP-ECog12 to discriminate CI from CU individuals was assessed using Receiver Operating Characteristic (ROC) curves. Area under the ROC curves (AUCs) between BHR and ADNI were compared using the DeLong test, as were AUCs between ECog12 and ECog in BHR.

Results: Online Self-ECog and SP-ECog scores effectively discriminated CI from CU with AUCs of 0.722 and 0.818, respectively. Similarly the abbreviated online versions, Self-ECog12 and SP-ECog12, also demonstrated discriminative ability (AUC = 0.709 and 0.777, respectively). When compared to in-clinic ECog scores, there were no significant differences in the ability to distinguish CI from CU between online and in-clinic versions (BHR Self-ECog AUC = 0.722 vs. ADNI Self-ECog AUC = 0.769, DeLong's $P = .06$; BHR SP-ECog AUC = 0.818 vs. ADNI SP-ECog AUC = 0.840, DeLong's $P = .50$). Additionally, comparison between online ECog and ECog12 showed no significant difference in AUCs (BHR Self-ECog AUC =

0.722 vs. BHR Self-ECog12 AUC = 0.709, DeLong's $P = .18$).

Conclusions: Online ECog scores, both full-length and short-form, were as valid as in-clinic ECog scores for identifying clinically diagnosed CI. Also, Self-ECog12 was as effective as full-length Self-ECog to identify CI in an online setting, offering a cost-effective and accessible screening tool for large-scale online. These results highlight the value of the online ECog as a valid tool for identifying older adults with CI in an online clinical study, facilitating early detection and referral for comprehensive evaluations for identifying potential candidates for disease-modifying therapy.

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Title**Evaluating the Accuracy of Online and In-Clinic Subjective Cognitive Decline Assessments in Detecting Cognitive Impairment: Multicohort Study**

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investigators can be found at:

http://adni.loni.usc.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf

Short title: Online ECog and ECOg12 predicts MCI



Abstract

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Results Online Self-ECog and SP-ECog scores effectively discriminated CI from CU with AUCs of 0.722 and 0.818, respectively. Similarly the abbreviated online versions, Self-ECog12 and SP-ECog12, also demonstrated discriminative ability (AUC = 0.709 and 0.777, respectively). When compared to in-clinic ECog scores, there were no significant differences in the ability to distinguish CI from CU between online and in-clinic versions (BHR Self-ECog AUC = 0.722 vs. ADNI Self-ECog AUC = 0.769, DeLong's $P = .06$; BHR SP-ECog AUC = 0.818 vs. ADNI SP-ECog AUC = 0.840, DeLong's $P = .50$). Additionally, comparison between online ECog and ECog12 showed no

significant difference in AUCs (BHR Self-ECog AUC = 0.722 vs. BHR Self-ECog12 AUC = 0.709, DeLong's $P = .18$).

Conclusions Online ECog scores, both full-length and short-form, were as valid as in-clinic ECog scores for identifying clinically diagnosed CI. Also, Self-ECog12 was as effective as full-length Self-ECog to identify CI in an online setting, offering a cost-effective and accessible screening tool for large-scale online. These results highlight the value of the online ECog as a valid tool for identifying older adults with CI in an online clinical study, facilitating early detection and referral for comprehensive evaluations for identifying potential candidates for disease-modifying therapy.

Keywords: Subjective cognitive decline, Everyday Cognition scale, ECog-12, online, MCI, dementia

Introduction

Dementia is a syndrome characterized by cognitive and non-cognitive symptoms, affecting activities of daily living. Alzheimer's disease (AD) is the most common cause of dementia, marked by amyloid beta and tau neuropathology, which leads to memory decline and other cognitive symptoms that precede dementia [1]. The recent development of disease-modifying medications such as aducanumab, lecanemab, and donanemab has brought new therapeutic options into clinical practice [2]. Consequently, identifying individuals likely to have mild cognitive impairment (MCI)—potential candidates for disease-modifying therapy—has become increasingly important.

Neuropsychological tests are widely used as diagnostic tools for cognitive impairment (CI), differentiating between cognitively unimpaired (CU) individuals, those with MCI, and those with dementia [3]. However, these tests are time-consuming, require trained professionals, and may not effectively capture fluctuations or progressive changes in cognitive function [4]. The Everyday Cognition scale (ECog), developed by Farias et al., offers a practical, time-efficient alternative that can be self-administered, focusing on realistic assessments of daily functioning [5]. A key feature of the ECog is its ability to assess subjective cognitive changes compared to 10 years ago, accounting for individual differences in baseline cognitive function. Additionally, it can address anosognosia—a common issue in individuals with MCI—through informant-administered ECog, which correlates more closely with clinical diagnoses than self-administered ECog [5-7]. Past studies have demonstrated the utility of ECog in identifying people with CI or AD pathology and predicting future conversion to MCI or dementia in healthy older adults [5-10].

Despite its proven effectiveness in clinical settings, the potential of ECog in remote, unsupervised formats remains underexplored. The Alzheimer's Disease Neuroimaging Initiative (ADNI) [11] recently began remote, unsupervised administration of the ECog12, a validated short form of the ECog [7, 8], to participants and their study partners (SP) [12]. This shift to digital platforms marks a significant advancement in clinical research, allowing for broader reach and more

continuous data collection [12]. Similarly, the Brain Health Registry (BHR), which has remotely administered ECog to over 64,680 participants since 2014 [13], exemplifies the potential of online platforms to facilitate large-scale cognitive assessments and long-term monitoring. These platforms [13-15] present significant advantages for identifying individuals at risk of cognitive decline, including the cost- and time-effectiveness of reducing in-person visits. Our study specifically investigates the validity and utility of the online ECog as compared to their traditional, in-clinic counterparts.

The overall goal of this study was to determine the ability of the online ECog to distinguish CI from CU individuals. We investigated three hypotheses: (1) the online ECog will be associated with clinically diagnosed CI; (2) the online ECog will show comparable association with CI as the in-clinic ECog; and (3) the online ECog12 will be as effective in identifying CI as the full-length online ECog. These hypotheses were tested by estimating associations between ECog and clinical diagnosis and comparing the accuracy of in-clinic versus online ECog and ECog12 versus the full ECog to distinguish diagnostic groups.

Methods and Materials

Participants

Participants in this study were recruited from two sources: the BHR Electronic Validation of Online Methods to Predict and Monitor Cognitive Decline (eVAL) study [16, 17] for the online component, and the ADNI study for the in-clinic component.

BHR eVAL

The BHR is an online neuroscience registry dedicated to the evaluation and monitoring of various cognitive disorders in a remote setting. Participants and their invited study partners visit the BHR website to complete remote cognitive assessments every six months [7]. The eVAL study is a multisite study that used the BHR platform to validate electronic versions of existing in-clinic cognitive monitoring instruments through the internet-based BHR platform. All eVAL participants were also evaluated in an in-clinic setting [18]. Participants enrolled in eVAL from BHR at UCSF and the Alzheimer's Disease Research Centers at the University of Alabama at Birmingham, Mayo Clinic in Rochester, MN, and Washington University [18].

ADNI

Data used in the preparation of this article were obtained from the ADNI database (adni.loni.usc.edu). Launched in 2003 as a collaboration between public and private sectors under the leadership of Principal Investigator Dr. Michael W. Weiner, ADNI aims to determine if serial magnetic resonance imaging, positron emission tomography scans, other biological markers, along with clinical and neuropsychological evaluations can effectively track the progression of MCI and early AD. For the latest updates, visit www.adni-info.org.

Inclusion criteria

This study included participants from BHR eVAL and ADNI with following criteria: i) age between 55-90 years; ii) have completed Self-ECog or SP-ECog questionnaire, or both; iii) have a clinical diagnosis of CU or MCI; iv) underwent both ECog questionnaire and clinical diagnostic evaluation

at the baseline evaluation period.

Ethical Considerations

This study was approved by the Institutional Review Board (IRB) of UCSF. Participants provided online informed consent upon enrollment in the BHR and written informed consent at their first in-clinic visit for enrollment in the eVAL study. For the ADNI study, all study protocols were approved by the IRB of the respective participating study centers, and participants provided written informed consent. All data was anonymized. Compensation for participation varied depending on the level and duration of involvement, ranging from \$0 to \$3,125 over a five-year period (<https://support.adni4.org/>).

Measurement

Everyday Cognition Scale

This study utilized baseline ECog scores from all participants. ECog is a 39-item questionnaire that assesses subjective changes in cognition and instrumental activities of daily living compared to 10 years ago [5]. Each item is rated on a 1-4 Likert scale (1, no change or better; 2, questionable or occasionally worse; 3, consistently a little worse; 4, consistently much worse), with the total score being the average of all responses and higher scores indicating greater decline. ECog ratings can be provided either by the individual themselves (self-reported ECog or Self-ECog) or by a SP (SP-ECog). In this study, SP-ECog was used when available. ECog was assessed in an online unsupervised setting in BHR eVAL study and in in-clinic setting in ADNI study.

ECog12 is a short form of ECog that was developed using selected 12 items throughout all cognitive domains [8]. ECog12 has shown a reduced testing time with high consistency and clinical validity, and several previous studies have used the ECog12 [6, 8, 19]. For this study, the full ECog was administered in both BHR and ADNI. We derived the ECog12 score from the full ECog by selecting the 12 items from the original, full-length instrument, and taking the average of the 12

items.

Clinical diagnosis

All participants in this study underwent clinical diagnostic evaluations. In the BHR eVAL study, participants were clinically diagnosed as CU, having MCI, or very mild dementia according to the Uniform Data Set version 3. This standard was developed by the National Alzheimer's Coordinating Center under the supervision of the National Institute on Aging and is implemented across all U.S. Alzheimer's Disease Centers [20].

In ADNI, participants were evaluated for an initial diagnosis using scores from the Clinical Dementia Rating scale (CDR), the Mini Mental State Exam, as well as clinical judgement. Participants were categorized into baseline diagnostic categories as follows: Cognitively Normal across all ADNI phases (1/GO/2/3), Subjective Memory Concern (SMC) in ADNI 2, Early MCI (EMCI) and Late MCI (LMCI) in ADNI GO/2, MCI in ADNI 1/3, and AD across all ADNI phases. For this study, Cognitively Normal, SMC, and MCI (EMCI, LMCI, and MCI) participants were included.

Clinical diagnoses in this study were categorized into two groups: CU, which includes CU from the BHR eVAL study and Cognitively Normal and SMC from ADNI; and CI, which includes MCI and very mild dementia from the BHR eVAL study and Early MCI, Late MCI, and MCI from ADNI study.

Demographic and clinical information

Participants' demographic and clinical information were included in this study: age at baseline, gender (male and female), years of education, race (African American, Asian, Caucasian, and Other [American Indian/Alaskan Native, Hawaiian/Other Pacific Islander, more than one, and unknown/declined to state race]).

Baseline CDR was obtained from both cohorts [21]. We used the CDR sum of box score, which is a reliable and valid diagnostic and dementia staging measure [22], with higher scores

indicating a greater level of CI. Geriatric Depression Scale-Short Form (GDS) was also obtained for both studies [23]. One GDS item regarding memory symptoms ("Do you feel you have more problems with memory than most?") was excluded from the GDS score, thus making the total score ranging from 0 to 14. A higher score indicates more depressive symptoms. Self-reported memory concern was also obtained from both cohorts and was a yes-or-no question: "Are you concerned that you have a memory problem?" in BHR eVAL and "Are you concerned that you have a memory or other thinking problem?" in ADNI.

Statistical analysis

Descriptive analysis

We produced descriptive statistics according to the diagnostic groups (CU and CI) and online or in-clinic study setting (BHR and ADNI) and compared demographic and clinical information and ECog scores between groups using independent t-test and chi-squared test.

Ability of online ECog for predicting CI

To test the first hypothesis that the online ECog can distinguish diagnostic groups, we performed binomial logistic regression analyses with the diagnostic group (CU or CI) as the dependent variable. We then calculated the area under the curve (AUC) using Receiver Operating Characteristic curve. Subsequent metrics including optimal ECog cut point score, sensitivity, specificity, and Youden index were also calculated. Additionally, adjusted AUCs based on the predicted value of a logistic model with ECog score, age, gender, years of education, race, and GDS were calculated.

Comparison between online and in-clinic ECog

To compare the ability of online ECog for discriminating CI from CU to that of in-clinic ECog, we compared the AUC for discriminating CI from CU in BHR to the AUC in ADNI using the DeLong test.

Comparison between ECog12 and ECog in online setting

To compare the effectiveness of online ECog12 in distinguishing CI from CU to the full-length online ECog, we also compared the AUC of ECog12 and AUC of full-length ECog in BHR. Statistical significance was set at $P < .05$, there was no correction for multiple comparisons, and R version 4.3.2 (R Core Team, 2023) was used in all analyses.

Results

Participants

Demographic and clinical information

A total of 1,801 participants were included in this study ($n = 428$ in BHR; $n = 1,373$ in ADNI). Table 1 presents the demographic and clinical information of participants, including comparisons across diagnostic groups and between the BHR and ADNI cohorts. Differences between CU and CI were observed in gender ($\chi^2 = 6.01$, $P = .014$), CDR sum of boxes ($t = -7.37$, $P < .001$), and self-reported memory concern ($t = 37.62$, $P < .001$) in BHR. In ADNI, differences were found in all demographic and clinical variables except for age. BHR participants showed higher GDS scores in both CU ($t = 14.51$, $P < .001$) and CI ($t = 5.80$, $P < .001$) groups compared to ADNI.

ECog scores in both groups

Table 1 displays ECog scores. In all cases, Self-ECog scores tended to be higher than SP-ECog scores although not statistically proven. The only significant difference between ADNI and BHR was observed in Self-ECog scores within the CI group (ADNI > BHR; $t = -2.21$, $P = .03$).

Association between ECog scores and CI

Table 2 presents the AUC values for distinguishing CI from CU in BHR and ADNI. The AUCs were moderate in BHR (0.709 – 0.818) and ADNI (0.747 – 0.840). After adjusting for age, gender, years of education, race, and GDS, the AUCs remained fair to moderate in both BHR and ADNI (0.724 – 0.851). Subsequent metrics including optimal cut point, sensitivity, specificity, and diagnostic accuracy are also presented in Table 2 for both studies.

Comparing AUCs between BHR and ADNI

Figure 1A and 1B illustrate the AUCs of BHR and ADNI and their comparisons. Both Self-ECog (BHR AUC = 0.722 [Confidence interval = 0.660-0.783], ADNI AUC = 0.769 [Confidence interval

= 0.743-0.792], DeLong $P = .16$) and SP-ECog (BHR AUC = 0.818 [Confidence interval = 0.759-0.878], ADNI AUC = 0.840 [Confidence interval = 0.819-0.860], DeLong $P = .50$) showed comparable AUC values between BHR and ADNI.

Comparing AUCs between ECog and ECog12 in BHR

Figure 1C and 1D depict the comparison between ECog and ECog12 in BHR. Self-ECog and Self-ECog12 demonstrated comparable AUCs (Self-ECog AUC = 0.722, Self-ECog12 AUC = 0.709, DeLong $P = .18$), while SP-ECog exhibited higher AUC than SP-ECog12 (SP-ECog AUC = 0.818, SP-ECog12 AUC = 0.777, DeLong $P = .001$)

Discussion

Principal Results

This study investigated the effectiveness of a measure of subjective cognitive decline, ECog, to detect CI in two cohorts: online in BHR and in-clinic in ADNI. The first finding was that the ECog demonstrated moderate accuracy in distinguishing CI and CU individuals in both BHR and ADNI. The second finding was that the online ECog in BHR showed comparable ability to detect CI, similar to the in-clinic ECog scores in ADNI. The third finding was that the ECog12, the short form of the ECog, was as effective as the full-length ECog for detecting CI in the BHR. These results indicate that ECog scores, whether administered online or in-clinic, and in both short-form and full-length versions, are useful in identifying clinically diagnosed CI individuals.

The first finding of this study is that the online ECog demonstrated a moderate association with CI. Both online Self- and SP-ECog scores effectively distinguished clinically diagnosed MCI individuals and CU individuals. This result aligns with previous research that has shown a strong association between online SP-ECog and self-reported diagnoses of MCI or AD [7]. Unlike prior research that relied solely on either online data [7, 24] or in-clinic data [6, 8, 9], our analysis included individuals with both online ECog data and clinical evaluations, allowing for a more rigorous assessment of the relationship between online subjective cognitive decline and objectively diagnosed CI. This finding highlights the potential clinical utility of online subjective cognitive decline measures, suggesting that they may reflect underlying CI as determined by expert clinical evaluation. Previous in-clinic studies have reported that informant-reported ECog scores are better at predicting CI from CU than self-reported scores [6, 8, 9]. A prior study focusing on older adults with CI found that online SP-ECog could distinguish AD dementia from MCI, while Self-ECog could not [25]. The ability of both Self- and SP-ECog to identify CI in this study might be due to the fact that most participants in BHR had mild cognitive symptoms [26], which makes it less likely that they are unaware of their cognitive status [27]. It is also noteworthy that establishing online ECog cut point

scores with good sensitivities, specificities, and accuracies is useful as a screening tool to detect CI in the older adult population. Our findings demonstrate the utility of online ECog for detecting the clinical diagnosis of CI, particularly in mildly impaired populations.

The second finding is that online ECog and in-clinic ECog produced comparable results in discriminating CI from CU. Previous studies have found that online ECog scores closely correspond with in-clinic ECog scores [28]. Our study newly revealed that online ECog is as effective as in-clinic ECog for detecting CI from CU, as demonstrated by the AUC comparison, which showed no significant difference between the two measures. This finding suggests that online ECog can serve as a viable alternative to in-clinic ECog for cognitive screening, expanding accessibility to cognitive assessments beyond traditional clinical settings. The trend towards overall higher discriminative AUC values, although not significant, in ADNI compared to BHR might be attributed to the nature of online scales, including response quality, lower engagement due to convenience, and potential technical issues [29-31]. From a clinical perspective, however, the lack of statistical significance in the AUC comparison suggests that both online and in-clinic ECog can be considered equally effective for CI screening, with the online version offering the added benefits of convenience and accessibility, particularly in populations with limited access to in-person assessments.

The third finding is that Self-ECog12 performed comparably to full-length Self-ECog in distinguishing CI from CU in an online setting. ECog12, derived from the original 39-item ECog, maintains good psychometric properties for various cognitive domains, including memory, visuospatial function, language, and executive function [8]. Previous studies have shown that ECog12 is as effective as full-length ECog in identifying the risk of MCI [6, 9]. The fact that online ECog12 shows a similar association with the diagnosis of CI versus CU as the 39-item ECog supports its use in online clinical studies like BHR. Recent large-scale neuroscience studies have started collecting online data from questionnaires about cognitive function, leveraging extensive and longitudinal collections [32-34]. ADNI4, the current phase of ADNI, also recently implemented

online ECog12 in a novel online screening approach to aid in selecting participants for plasma AD biomarker analysis and in-clinic evaluation [12, 19]. However, SP-ECog12 showed a significantly lower probability of detecting CI from CU compared to SP-ECog in this study, although both SP-ECog and SP-ECog12 showed moderate AUCs. We believe this discrepancy may be due to the brevity and the reduced amount of information collected by SPs in the online ECog12. This might be further supported by the fact that SPs, who may not know the participants well or see them frequently, can still take part in the BHR study [7]. Nevertheless, the online ECog12 remains a useful and time-efficient tool for identifying individuals at risk of MCI in online settings.

Recently, advances in online technology have allowed the use of online cognitive tests to identify CI with convenience and scalability [35, 36]. Self-administered online digital neuropsychological tests are an effective method for identifying CI, offering benefits such as accessibility, efficiency, and diagnostic accuracy for dementia [37]. Many well-known in-clinic tests, including the Montreal Cognitive Assessment, Cogstate Brief Battery, and Cambridge Neuropsychological Test Automated Battery (CANTAB®), have been adapted for online use [38-41]. Although neuropsychological tests objectively measure cognitive abilities through rigorous standardized tasks, ECog, which is a brief measure of subjective cognitive decline, captures an individual's or their informant's perception of cognitive and functional changes over the past 10 years in real-life. This can provide early indicators of cognitive decline that objective tests might miss [5, 27]. As ECog and ECog12 can be easily administered online with validity for identifying CI from CU, integrating both objective and subjective measure of cognitive decline in online studies could enhance early detection of MCI who are potential candidates for disease-modifying therapy and comprehensive understanding of cognitive health.

Limitations

This study has several limitations. Firstly, the BHR eVAL study and ADNI consists

predominantly of participants with over 16 years of education, 85% of whom are non-Latinx white. This lack of demographic diversity likely limits the generalizability of the findings and introduces bias related to differences in race, ethnicity, cognitive reserve, and socioeconomic status—factors that can influence the diagnosis, prognosis, and treatment response in dementia. African American and Latinx older adults are up to 1.5 to 2 times more likely to develop AD and/or AD-related dementias compared to White older adults [42]. These disparities may stem from differences in medical risk factors for AD (e.g., depression, diabetes, obesity, hypertension), biological factors (e.g., genetics, epigenetics, or proteomic markers), factors contributing to cognitive reserve (e.g., education and occupation), and non-biological or social factors (e.g., economic stability, safety, housing, environment) [12]. Additionally, BHR has limitations, including selection bias, low data integrity, informant variability, and high dropout rates. Participants are more likely to have higher digital proficiency and increased awareness of cognitive health issues, further skewing the representativeness of the sample. On the other hand, online studies offer the advantage of scalability, enabling participation from individuals who might otherwise be unable to join due to geographic or time constraints. However, challenges such as data inaccuracy, missing information, and the inability to verify whether participants completed assessments independently or with assistance remain. Another important limitation is the difficulty in managing participant dropout over time. Prior studies have also shown that non-white or Latinx individuals, as well as those with lower educational attainment, are more likely to discontinue participation in follow-up assessments in online settings [43]. These patterns highlight the need for more inclusive recruitment strategies and efforts to retain diverse populations in future studies to ensure findings are more broadly applicable.

The second limitation is that this study was not originally designed to compare online and in-clinic populations. Instead, it compared these populations retrospectively, meaning that the recruitment process was not perfectly controlled from the outset and there may be participation self-selection biases. Thirdly, the cross-sectional design of this study limits the interpretation of the

results due to the lack of longitudinal cause-and-effect relationships between ECog scores and clinical diagnoses. Fourthly, the lack of correction for multiple comparisons is an additional limitation of the study.

Conclusions

This study highlights the value of online ECog as an effective and scalable tool for identifying older adults at risk of MCI, particularly in online clinical settings. Subjective cognitive changes measured in a remote, unsupervised, online setting distinguished CI from CU diagnostic groups with moderate accuracy. Compared to in-clinic scales, the online ECog showed comparable ability to discriminate CI from CU. ECog12, a shorter form developed to increase brevity, also demonstrated a moderate association with clinical diagnosis in an online setting. These results highlight the value of the online ECog as a valid tool for identifying older adults with MCI in an online clinical study, facilitating early detection and referral for more comprehensive evaluations in both research and clinical settings.

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6 Conflict of interest

Manchumad Manjavong, Adam Diaz, Miriam T. Ashford, Anna Aaronson, Joseph Eichenbaum, R. Scott Mackin, Rachana Tank, Melanie J. Miller, Bernard Landavazo, Erika Cavallone, Diana Truran, Monica R. Camacho, Juliet Fockler, Derek Flenniken, and Sarah Tomaszewski Farias report nothing to disclose; Jae Myeong Kang reports grants from Gachon University, during the conduct of the study; Rachel Nosheny reports grants from NIA, during the conduct of the study; Michael Weiner reports grants from National Institutes of Health (NIH)/NINDS/National Institute on Aging, grants from Department of Defense (DOD), grants from California Department of Public Health (CDPH), grants from University of Michigan, grants from Siemens, grants from Biogen, grants from Hillblom Foundation, grants from Alzheimer's Association, grants from Johnson & Johnson, grants from Kevin and Connie Shanahan, grants from GE, grants from VUmc, grants from Australian Catholic University, grants from The Stroke Foundation, grants from Veterans Administration, personal fees from Boxer Capital, personal fees from Cerecin, personal fees from Clario, personal fees from Dementia Society of Japan, personal fees from Eisai, personal fees from Guidepoint, personal fees from Health and Wellness Partners, personal fees from Indiana University, personal fees from LCN Consulting, personal fees from Merck SharP & Dohme Corp., personal fees from NC Registry for Brain Health, personal fees from Prova Education, personal fees from T3D Therapeutics, personal fees from University of Southern California (USC), personal fees from WebMD, personal fees from China Association for Alzheimer's Disease (CAAD), personal fees from Taipei Medical University, personal fees from AD/PD Congress, personal fees from Cleveland Clinic, personal fees from CTAD Congress, personal fees from Foundation of Learning, personal fees from Health Society (Japan), personal fees from INSPIRE Project; U. Toulouse, personal fees from Japan Society for Dementia Research, personal fees from Korean Dementia Society, personal fees from National Center for Geriatrics and Gerontology (NCGG; Japan), personal fees from University of Southern California (USC), other from Alzeca, other from Alzheon, other from ALZ Path, other from Anven, outside the

submitted work.

7 Abbreviations

AD, Alzheimer's disease; AUC, area under curve; ADNI, Alzheimer's Disease Neuroimaging Initiative; BHR, Brain Health Registry; CDR-SOB, Clinical Dementia Rating-Sum of Boxes; CI, cognitively impaired; CU, cognitively unimpaired; eCDR, Electronic Clinical Dementia Rating; ECog, Everyday Cognition Scale; ECog12, short version of ECog; eVAL, Electronic Validation of Online Methods to Predict and Monitor Cognitive Decline; EMCI, Early Mild Cognitive Impairment; GDS, Geriatric Depression Scale; IRB, Institutional Review Board; LMCI, Late Mild Cognitive Impairment; MCI, Mild Cognitive Impairment; Self-ECog, self-reported ECog; SP-ECog, study partner-reported ECog; ROC, Receiver Operating Characteristic; SMC, Subjective Memory Concern

8 Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

9 References

1. Jack CR, Jr., Bennett DA, Blennow K, Carrillo MC, Dunn B, Haeberlein SB, et al. NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. *Alzheimers Dement*. 2018 Apr;14(4):535-62. PMID: 29653606. doi: 10.1016/j.jalz.2018.02.018.
2. Cummings J, Zhou Y, Lee G, Zhong K, Fonseca J, Cheng F. Alzheimer's disease drug development pipeline: 2024. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*. 2024;10(2):e12465. doi: <https://doi.org/10.1002/trc2.12465>.
3. Lezak MD. *Neuropsychological assessment*: Oxford University Press, USA; 2004. ISBN: 0195111214.
4. Harvey PD. Clinical applications of neuropsychological assessment. *Dialogues in clinical neuroscience*. 2012;14(1):91-9.
5. Farias ST, Mungas D, Reed BR, Cahn-Weiner D, Jagust W, Baynes K, et al. The measurement of everyday cognition (ECog): scale development and psychometric properties. *Neuropsychology*. 2008;22(4):531.
6. van Harten AC, Mielke MM, Swenson-Dravis DM, Hagen CE, Edwards KK, Roberts RO, et al. Subjective cognitive decline and risk of MCI: The Mayo Clinic Study of Aging. *Neurology*. 2018 Jul 24;91(4):e300-e12. PMID: 29959257. doi: 10.1212/wnl.0000000000005863.
7. Nosheny RL, Camacho MR, Insel PS, Flenniken D, Fockler J, Truran D, et al. Online study partner-reported cognitive decline in the Brain Health Registry. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*. 2018 2018/01/01;4:565-74. doi: <https://doi.org/10.1016/j.trci.2018.09.008>.
8. Tomaszewski Farias S, Mungas D, Harvey DJ, Simmons A, Reed BR, Decarli C. The measurement of everyday cognition: development and validation of a short form of the Everyday Cognition scales. *Alzheimers Dement*. 2011 Nov;7(6):593-601. PMID: 22055976. doi: 10.1016/j.jalz.2011.02.007.
9. Rueda AD, Lau KM, Saito N, Harvey D, Risacher SL, Aisen PS, et al. Self-rated and informant-rated everyday function in comparison to objective markers of Alzheimer's disease. *Alzheimer's & Dementia*. 2015;11(9):1080-9.
10. Manjavong M, Diaz A, Ashford M, Aaronson A, Miller M, Kang J, et al. Performance of a Short Version of the Everyday Cognition Scale (ECog-12) to Detect Cognitive Impairment. *The Journal of Prevention of Alzheimer's Disease*. 2024;1-10.
11. Petersen RC, Aisen PS, Beckett LA, Donohue MC, Gamst AC, Harvey DJ, et al. Alzheimer's Disease Neuroimaging Initiative (ADNI): clinical characterization. *Neurology*. 2010 Jan 19;74(3):201-9. PMID: 20042704. doi: 10.1212/WNL.0b013e3181cb3e25.
12. Weiner MW, Veitch DP, Miller MJ, Aisen PS, Albala B, Beckett LA, et al. Increasing participant diversity in AD research: Plans for digital screening, blood testing, and a community-engaged approach in the Alzheimer's Disease Neuroimaging Initiative 4. *Alzheimer's & Dementia*. 2023;19(1):307-17. doi: <https://doi.org/10.1002/alz.12797>.
13. Weiner MW, Nosheny R, Camacho M, Truran-Sacrey D, Mackin RS, Flenniken D, et al. The Brain Health Registry: an internet-based platform for recruitment, assessment, and longitudinal monitoring of participants for neuroscience studies. *Alzheimer's & Dementia*. 2018;14(8):1063-76.
14. Reiman EM, Langbaum J, Fleisher AS, Caselli RJ, Chen K, Ayutyanont N, et al. Alzheimer's Prevention Initiative: a plan to accelerate the evaluation of presymptomatic treatments. *Journal of Alzheimer's Disease*. 2011;26(s3):321-9.
15. Walter S, Clanton TB, Langford OG, Rafii MS, Shaffer EJ, Grill JD, et al. Recruitment into the Alzheimer Prevention Trials (APT) Webstudy for a Trial-Ready Cohort for Preclinical and Prodromal Alzheimer's Disease (TRC-PAD). *J Prev Alzheimers Dis*. 2020;7(4):219-25. PMID: 32920623. doi: 10.14283/jpad.2020.46.
16. Nosheny RL, Yen D, Howell T, Camacho M, Moulder K, Gummadi S, et al. Evaluation of the Electronic Clinical Dementia Rating for Dementia Screening. *JAMA Network Open*.

2023;6(9):e2333786-e.

17. Weiner MW, Aaronson A, Eichenbaum J, Kwang W, Ashford MT, Gummadi S, et al. Brain health registry updates: An online longitudinal neuroscience platform. *Alzheimer's & Dementia*. 2023;19(11):4935-51.
18. Howell T, Gummadi S, Bui C, Santhakumar J, Knight K, Roberson ED, et al. Development and implementation of an electronic clinical dementia rating and financial capacity instrument-short form. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*. 2022;14(1):e12331.
19. Miller MJ, Weiner MSW, Nosheny RL, Albala B, Mindt MR, Okonkwo O, et al. ADNI4's novel remote screening approach - weighing priorities in participant selection. *Alzheimer's & Dementia*. 2023;19(S18):e075152. doi: <https://doi.org/10.1002/alz.075152>.
20. Besser L, Kukull W, Knopman DS, Chui H, Galasko D, Weintraub S, et al. Version 3 of the National Alzheimer's Coordinating Center's Uniform Data Set. *Alzheimer Disease & Associated Disorders*. 2018;32(4):351-8. PMID: 00002093-201810000-00015. doi: 10.1097/wad.0000000000000279.
21. Morris JC. Clinical dementia rating: a reliable and valid diagnostic and staging measure for dementia of the Alzheimer type. *International psychogeriatrics*. 1997;9(S1):173-6.
22. Williams MM, Storandt M, Roe CM, Morris JC. Progression of Alzheimer's disease as measured by Clinical Dementia Rating Sum of Boxes scores. *Alzheimer's & Dementia*. 2013;9(1):S39-S44.
23. Leshner EL, Berryhill JS. Validation of the geriatric depression scale-short form among inpatients. *Journal of clinical psychology*. 1994;50(2):256-60.
24. Kang JM, Manjavong M, Jin C, Diaz A, Ashford MT, Eichenbaum J, et al. Subjective cognitive decline predicts longitudinal neuropsychological test performance in an unsupervised online setting in the Brain Health Registry. *Alzheimer's Research & Therapy*. 2025/01/07;17(1):10. doi: 10.1186/s13195-024-01641-2.
25. Nosheny RL, Camacho MR, Jin C, Neuhaus J, Truran D, Flenniken D, et al. Validation of online functional measures in cognitively impaired older adults. *Alzheimer's & Dementia*. 2020;16(10):1426-37. doi: <https://doi.org/10.1002/alz.12138>.
26. Ashford MT, Aaronson A, Kwang W, Eichenbaum J, Gummadi S, Jin C, et al. Unsupervised Online Paired Associates Learning Task from the Cambridge Neuropsychological Test Automated Battery (CANTAB®) in the Brain Health Registry. *The Journal of Prevention of Alzheimer's Disease*. 2024 2024/03/01;11(2):514-24. doi: 10.14283/jpad.2023.117.
27. Orfei MD, Blundo C, Celia E, Casini AR, Caltagirone C, Spalletta G, et al. Anosognosia in mild cognitive impairment and mild Alzheimer's disease: frequency and neuropsychological correlates. *The American Journal of Geriatric Psychiatry*. 2010;18(12):1133-40.
28. Howell T, Neuhaus J, Glymour MM, Weiner MW, Nosheny RL, Alzheimer's Disease Neuroimaging I. Validity of Online Versus In-Clinic Self-Reported Everyday Cognition Scale. *The Journal of Prevention of Alzheimer's Disease*. 2022 2022/04/01;9(2):269-76. doi: 10.14283/jpad.2022.20.
29. McMaster HS, LeardMann CA, Speigle S, Dillman DA, Stander V, Pflieger J, et al. An experimental comparison of web-push vs. paper-only survey procedures for conducting an in-depth health survey of military spouses. *BMC Medical Research Methodology*. 2017 2017/04/26;17(1):73. doi: 10.1186/s12874-017-0337-1.
30. Couper MP. Web surveys: A review of issues and approaches. *The public opinion quarterly*. 2000;64(4):464-94.
31. Nulty DD. The adequacy of response rates to online and paper surveys: what can be done? *Assessment & evaluation in higher education*. 2008;33(3):301-14.
32. Davis KAS, Coleman JRI, Adams M, Allen N, Breen G, Cullen B, et al. Mental health in UK Biobank - development, implementation and results from an online questionnaire completed by 157 366 participants: a reanalysis. *BJPsych Open*. 2020 Feb 6;6(2):e18. PMID: 32026800. doi:

10.1192/bjo.2019.100.

33. Ritchie CW, Molinuevo JL, Truyen L, Satlin A, Van der Geyten S, Lovestone S. Development of interventions for the secondary prevention of Alzheimer's dementia: the European Prevention of Alzheimer's Dementia (EPAD) project. *Lancet Psychiatry*. 2016 Feb;3(2):179-86. PMID: 26683239. doi: 10.1016/s2215-0366(15)00454-x.
34. Ikram MA, Brusselle GG, Murad SD, van Duijn CM, Franco OH, Goedegebure A, et al. The Rotterdam Study: 2018 update on objectives, design and main results. *European journal of epidemiology*. 2017;32:807-50.
35. Chen L, Zhen W, Peng D. Research on digital tool in cognitive assessment: a bibliometric analysis. *Frontiers in Psychiatry*. 2023;14:1227261.
36. Watt JA, Lane NE, Veroniki AA, Vyas MV, Williams C, Ramkissoon N, et al. Diagnostic accuracy of virtual cognitive assessment and testing: Systematic review and meta-analysis. *Journal of the American Geriatrics Society*. 2021;69(6):1429-40. doi: <https://doi.org/10.1111/jgs.17190>.
37. Öhman F, Hassenstab J, Berron D, Schöll M, Papp KV. Current advances in digital cognitive assessment for preclinical Alzheimer's disease. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*. 2021;13(1):e12217. doi: <https://doi.org/10.1002/dad2.12217>.
38. Cormack FK, Morris H, Barnett JH, Housden C. P1-504: CANTAB MOBILE: EXPERIENCE OF USE OF A DIGITAL MEMORY ASSESSMENT TOOL IN UK PRIMARY CARE. *Alzheimer's & Dementia*. 2018;14(7S_Part_9):P522-P3. doi: <https://doi.org/10.1016/j.jalz.2018.06.515>.
39. Backx R, Skirrow C, Dente P, Barnett JH, Cormack FK. Comparing web-based and lab-based cognitive assessment using the Cambridge Neuropsychological Test Automated Battery: A within-subjects counterbalanced study. *Journal of Medical Internet Research*. 2020;22(8):e16792.
40. Cromer JA, Harel BT, Yu K, Valadka JS, Brunwin JW, Crawford CD, et al. Comparison of cognitive performance on the Cogstate brief battery when taken in-clinic, in-group, and unsupervised. *The Clinical Neuropsychologist*. 2015;29(4):542-58.
41. Snowden A, Hussein A, Kent R, Pino L, Hachinski V. Comparison of an electronic and paper-based Montreal Cognitive Assessment Tool. *Alzheimer Disease & Associated Disorders*. 2015;29(4):325-9.
42. Chen C, Zissimopoulos JM. Racial and ethnic differences in trends in dementia prevalence and risk factors in the United States. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*. 2018;4:510-20.
43. Ashford MT, Eichenbaum J, Williams T, Camacho MR, Fockler J, Ulbricht A, et al. Effects of sex, race, ethnicity, and education on online aging research participation. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*. 2020;6(1):e12028.

Supplementary Files

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Figures

Receiver operating curves for predicting cognitive impairment. AUC, area under curve; BHR, Brain Health Registry; ADNI, Alzheimer's Disease Neuroimaging Initiative; ECog, Everyday Cognition Scale; Self-ECog, self-reported ECog; SP-ECog, study partner-reported ECog; ECog12, short version of ECog.

