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Original Article

# Bridging the gap: A conversion framework for CDR-SB and MoCA scores in Alzheimer's disease and related dementia

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ABSTRACT

*Background:* Accurate assessment of cognitive impairment is essential to effective Alzheimer's disease (AD) management and research. However, the absence of validated methods to translate scores between widely used instruments—such as the Clinical Dementia Rating Scale Sum of Boxes (CDR-SB) in trials and the Montreal Cognitive Assessment (MoCA) in clinical practice—poses a significant barrier. This limits data harmonization, impedes cross-study comparability, and complicates the integration of clinical and research evidence. Bridging this gap is critical for consistent staging, longitudinal monitoring, and data-driven decision-making in AD and related dementias.

*Objectives:* To develop and validate bidirectional score conversion tables between CDR-SB and MoCA using a large, diverse cohort spanning the full spectrum of cognitive function.

*Design:* Retrospective, cross-sectional analysis using equipercentile equating with log-linear smoothing. Optimal smoothing parameters were selected by minimizing mean squared error, Akaike Information Criterion, and Bayesian Information Criterion. Concordance was assessed using Spearman's rank correlation and Bland-Altman plots.

*Setting:* National Alzheimer's Coordinating Center (NACC), aggregating standardized assessments from 35 U.S.-based Alzheimer's Disease Research Centers.

*Participants:* 23,717 individuals (59,871 visits) with same-day CDR-SB and MoCA assessments from January 2015 to September 2024, spanning normal cognition, mild cognitive impairment (MCI), and dementia.

*Intervention:* None; this was a secondary analysis of existing data.

*Measurements:* Primary measures included CDR-SB (0–18; higher = greater impairment) and MoCA (0–30; higher = better cognition). Bidirectional crosswalk tables were derived using equipercentile equating.

*Results:* CDR-SB and MoCA scores showed strong inverse correlation (Spearman's $\rho = -0.68$; $p < 0.001$). Crosswalk tables demonstrated good agreement across the cognitive spectrum and performed consistently in the full cohort and an AD-specific subgroup.

*Conclusions:* This study provides the first validated, bidirectional CDR-SB–MoCA crosswalk, supporting data harmonization and consistent interpretation of cognitive severity across research and clinical settings.

## 1. Introduction

Alzheimer's disease (AD) represents a growing global health crisis, with its prevalence expected to rise exponentially as populations age [1,2]. This neurodegenerative disorder imposes substantial burdens on patients, caregivers, healthcare systems, and society, with progressive cognitive and functional decline leading to significant morbidity, mortality, and economic costs [2–4]. In 2025, AD and related dementias are projected to impose an annual economic burden of $252 billion in formal care costs and up to $580 billion when including informal care in the United States [3], driven largely by direct medical expenses, long-term care, and productivity losses affecting patients and caregivers [3].

Early identification and accurate staging of AD are increasingly crucial, particularly with the advent of disease-modifying treatments (DMTs) targeting the underlying pathophysiology of AD [5,6]. These therapies show the greatest efficacy when administered in the earliest disease stages, specifically in mild cognitive impairment (MCI) and mild AD dementia [7], necessitating precise and reliable tools for patient identification. However, distinguishing these early stages in real-world clinical practice remains challenging, underscoring the need for stan-

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dardized, scalable cognitive assessment measures that align with both clinical trial endpoints and routine care [5].

The Clinical Dementia Rating Scale Sum of Boxes (CDR-SB) is a semi-structured global scale combining patient cognitive testing and caregiver-reported functional abilities across six domains (memory, orientation, judgment and problem solving, community affairs, home and hobbies, personal care) and yields a 0–18 score reflecting both cognition and function [8,9]. Unlike brief cognitive screening tools, CDR-SB captures subtle functional impairments that may precede overt cognitive deficits, making it essential for staging AD. It is the gold-standard outcome measure in clinical trials and is also employed in some longitudinal studies to enable precise staging of AD and related cognitive disorders [9–11].

In contrast, the Montreal Cognitive Assessment (MoCA) is a brief, structured cognitive screening tool administered directly to the patient, rather than a full neuropsychological battery. It assesses multiple cognitive domains, including executive function, memory, language, attention, visuospatial abilities, and orientation, with scores ranging from 0 to 30 [12,13]. The MoCA has demonstrated greater sensitivity than traditional instruments like the Mini-Mental State Examination (MMSE) [14]. MoCA is widely used in clinical settings for its ease of administration, particularly in the early stages of disease. However, it lacks the functional assessment component included in the CDR-SB, which offers a more comprehensive evaluation of real-world cognitive and functional impact. Moreover, MoCA scores are influenced by the patient's level of formal education [15], which can affect interpretability across populations.

The ability to translate scores between CDR-SB and MoCA has important implications for clinical decision-making, longitudinal research, and multicenter studies using different cognitive measures. Converting scores allows for more consistent interpretation of disease severity across patient populations and facilitates data harmonization. Prior studies have established conversion frameworks for other cognitive tests, such as MMSE and MoCA, using equipercentile equating [16], regression-based modeling [17], and machine learning approaches [18]. However, no widely accepted conversion method exists between CDR-SB and MoCA, limiting cross-study and clinical comparability.

Beyond direct clinical and research applications, the capacity to interconvert CDR-SB and MoCA scores has broader implications for healthcare policy, clinical trial design, and real-world evidence generation. Regulatory agencies and payers increasingly require standardized cognitive assessments to support drug approval and reimbursement decisions. A validated conversion framework would enable pharmaceutical companies and researchers to pool data from studies using different cognitive instruments, improving trial generalizability. Large-scale observational studies and electronic health record (EHR) analyses could also benefit by enabling retrospective data harmonization, facilitating meta-analyses, and improving disease progression modeling and patient stratification.

This study aims to develop a robust conversion framework between CDR-SB and MoCA scores using established statistical methodologies. By leveraging a well-characterized patient cohort, we seek to provide clinicians and researchers with an empirically derived conversion table that facilitates the integration of data across different assessment paradigms. This work enhances cognitive assessment interoperability, enabling more precise disease monitoring and informed therapeutic decisions. By improving communication among clinicians and researchers, it facilitates the comparison and pooling of findings, ultimately guiding evidence-based clinical and policy decisions on dementia and advancing Alzheimer's research.

## 2. Methods

### 2.1. Data source

The National Alzheimer's Coordinating Center (NACC) is the central data hub for the National Institute on Aging's Alzheimer's Disease Research Centers (ADRC) Program, which includes 35 centers across the U.S. NACC consolidates one of the largest datasets on AD and related dementias.

Prior to NACC's creation, data collection at ADRCs was fragmented, with each center using different methods and platforms. NACC standardized this process, launching the Uniform Data Set (UDS) in 2005 [19]. The UDS introduced annual cognitive, behavioral, and functional assessments, enhancing data quality, comparability, and research utility, while allowing for long-term tracking of cognitive decline and co changes.

All contributing ADRCs are required to obtain informed consent from participants and secure independent Institutional Review Board (IRB) approvals from their respective institutions prior to submitting data to NACC. The study was conducted in accordance with the ethical standards outlined in the 1964 Declaration of Helsinki and its subsequent amendments, or other comparable ethical guidelines. This study does not involve any new research with human participants or animals conducted by the authors.

### 2.2. Study population

We utilized the NACC UDS dataset to identify patients who underwent same-day cognitive assessments with both the CDR-SB and MoCA. The dataset spans from 2005 to September 1, 2024, though MoCA scores were introduced in 2015.

Patients were included if they had at least one visit where both the CDR-SB and MoCA were administered on the same day. Visits with incomplete or missing data for either measure were excluded to ensure consistency in cognitive performance assessment. The resulting cohort consisted of a large and diverse sample of individuals with varying cognitive statuses at the time of their first recorded visit.

As part of the ADRC/NACC research protocol, participants underwent comprehensive annual evaluations that included clinical, neurological, and neuropsychological assessments. Cognitive diagnoses—normal cognition, impaired-not-MCI (used for cases that did not clearly fit into normal or MCI categories), MCI, or dementia—were assigned at baseline and updated at each annual visit. These diagnoses were typically determined through a multidisciplinary consensus process at each site. However, as noted by NACC, some diagnoses may have been assigned by a single clinician, depending on individual ADRC protocols.

For participants diagnosed with a cognitive disorder, the NACC database also captures the presumptive primary etiologic diagnosis (e.g., Alzheimer's disease) and any contributing conditions. This detailed clinical and diagnostic information—alongside cognitive and genetic data—provides a strong foundation for evaluating cognitive trajectories and supports the development of crosswalks between CDR-SB and MoCA scores across diverse clinical presentations.

### 2.3. Statistical analysis

To evaluate the relationship between CDR-SB and MoCA scores, we calculated Spearman's rank correlation coefficient. Unlike Pearson's correlation, Spearman's method uses ranked values, allowing it to capture strictly monotonic relationships and making it suitable for both continuous and ordinal data [20]. This rank-based approach also enhances robustness against outliers [20].

Equipercentile equating was applied to establish score comparability between the CDR-SB and MoCA, ensuring that corresponding scores held the same relative position within their respective distributions. This nonparametric approach aligns the percentile rank distributions of two assessments, allowing scores to be considered equivalent if they occupy the same relative position within their distributions [21]. Equipercentile equating offers a more flexible approach to score alignment than linear equating, which assumes normality and equal variance. Unlike linear methods, it accommodates the complexities often observed in cognitive

assessments, including skewed distributions, floor and ceiling effects, and differing score ranges [21,22]. This technique adjusts not only for differences in mean and standard deviation but also for higher moments of the distribution, such as skewness and kurtosis, enabling more precise harmonization of instruments. By preserving the rank order of scores and accounting for response patterns that cluster at the high or low ends of the scale, equipercentile equating enhances comparability across cognitive assessments, facilitating more accurate cross-instrument interpretations.

The process of establishing crosswalks between the CDR-SB and MoCA begins by smoothing the discrete score distributions using log-linear transformation to produce more stable estimates of score probabilities. This smoothing process reduces irregularities in the score distribution and mitigates the impact of sampling variability and measurement error, ensuring more reliable and consistent results. To enhance the precision and accuracy of the conversion, the optimal degree of smoothing is determined by systematically evaluating polynomial degrees (0, 1, 2, 3, …) using mean squared error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The dataset is divided into training and test sets to validate the results and ensure generalizability. MSE, AIC, and BIC values are computed for each smoothing degree, and the optimal degree is selected based on the point where further increases provide minimal improvements in these metrics.

To implement the crosswalks, equipercentile linking methods are applied using the R package **"equate"** [16]. This method aligns the score distributions of the two assessments, facilitating the estimation of equivalent scores while accounting for differences in scale and measurement properties. The same approach is consistently applied to all conversions presented in this study. This includes a comprehensive overview of the criteria used to determine the optimal log-linear smoothing degree for each conversion, ensuring methodological rigor and reproducibility across all transformations.

Bland-Altman plot was used to graphically assess the agreement between the raw scores and the equivalent scores generated through the crosswalk [23]. By plotting the differences against the mean of the two scores, this method allows for a direct visualization of the average agreement and potential systematic bias across the score range. The mean difference (bias) and limits of agreement provide an intuitive assessment of whether the linking function produces scores comparable to the original measure across the full score distribution, highlighting areas of good agreement or potential discrepancies.

Once the score distributions are smoothed, the cumulative distribution functions (CDFs) of CDR-SB and MoCA are aligned to ensure that percentile ranks correspond accurately between the two assessments. This alignment process allows scores on one scale to be directly mapped to equivalent scores on the other, preserving the relative ranking of individuals within their respective populations. Conversion tables are then generated through inverse percentile matching, enabling direct score translation while maintaining the integrity of score distributions.

This method has been effectively used to equate scores between MoCA and MMSE [17,24,25], as well as other cognitive tests, allowing for continuity in longitudinal studies and facilitating comparisons across different studies and populations.

## 3. Results

### 3.1. Descriptive statistics

The study cohort included a diverse sample of individuals who underwent cognitive assessments with both the CDR-SB and MoCA on the

**Table 1**
Baseline demographic and clinical characteristics of the cohort.

| | Full Cohort | | | | Alzheimer's Disease | | |
|---|---|---|---|---|---|---|---|
| **Cohort** | *NC* | *MCI* | *Dem* | *CI* | *MCI* | *Dem* | *CI* |
| Number of Patients | 11,846 | 5349 | 5438 | 1084 | 3018 | 3926 | 177 |
| Age | 69.4 (10.8) | 72.1 (9.2) | 71.4 (10.3) | 69.9 (10.5) | 73.4 (8.6) | 72.7 (10.2) | 75.2 (9.1) |
| Education | 16.1 (2.8) | 15.7 (3.1) | 15.4 (3.2) | 15.3 (3.1) | 15.9 (3.1) | 15.3 (3.3) | 16 (2.9) |
| CDR-SB | 0.1 | 1.4 | 5.6 | 0.7 | 1.4 | 5.7 | 0.7 |
| MOCA | 26.2 | 22.2 | 15 | 23.8 | 21.8 | 14.4 | 24.7 |
| Female (%) | 65.2 | 49.6 | 48.5 | 59.5 | 50.3 | 53.1 | 54.2 |
| White (%) | 77 | 77.3 | 87.2 | 66.1 | 79.4 | 86.3 | 85.3 |
| Black (%) | 16.7 | 17.3 | 7.6 | 27.1 | 15.7 | 8.5 | 11.9 |
| APOE – *homozygous* (%) | 2.8 | 6.1 | 8.7 | 2.1 | 8.4 | 11 | 3.4 |
| APOE – *heterozygous* (%) | 23 | 28 | 32.4 | 23.1 | 31.1 | 36.4 | 22 |
| APOE – *non-Carrier* (%) | 53.6 | 44 | 37.9 | 51.9 | 40 | 32.6 | 59.3 |
| CDR-SB range | [0 - 11] | [0 - 10] | [0 - 18] | [0 – 7.5] | [0 – 10] | [0 – 18] | [0 - 3.5] |
| MOCA range | [10 - 30] | [4 - 30] | [0 - 30] | [5 - 30] | [5–30] | [0 – 30] | [13–30] |
| **Diagnoses (%)** | | | | | | | |
| Neurodegenerative Disorders with CI | - | 73.1 | 94.8 | 33.3 | | | |
| *Alzheimer's Disease (AD)* | - | *54.8* | *73.9* | *20* | | | |
| *Lewy Body Disease (LBD)* | - | *6.1* | *7.2* | *4* | | | |
| *Frontotemporal Disorders (FTD)* | - | *3* | *11.3* | *2.4* | | | |
| *Vascular Dementia* | - | *9.2* | *2.4* | *6.9* | | | |
| Cognitive Impairment Due to External Factors | - | 12.3 | 1.2 | 32.3 | | | |
| *Traumatic Brain Injury (TBI)* | - | *1.1* | *0.4* | *2* | | | |
| *CNS Neoplasm* | - | *0.1* | *0* | *0.2* | | | |
| *CI Due to Alcohol and Substance Abuse* | - | *0.5* | *0.1* | *1* | | | |
| *CI Due to Systemic Disease* | - | *2* | *0.1* | *4.2* | | | |
| *CI Due to Medications* | - | *0.4* | - | *2* | | | |
| *CI Due to Others* | - | *8.2* | *0.6* | *22.9* | | | |
| Psychiatric and Behavioral Disorders | - | 1.9 | 0 | 8.3 | | | |
| *Bipolar Disorder* | - | *0.2* | *0* | *1.6* | | | |
| *Schizophrenia or Other Psychosis* | - | *0.2* | *0* | *0.5* | | | |
| *Anxiety Disorder* | - | *0.9* | *0* | *3.6* | | | |
| *Post-Traumatic Stress Disorder (PTSD)* | - | *0.1* | - | *0.9* | | | |
| *Other Psychiatric Disease* | - | *0.5* | *0* | *1.7* | | | |
| Others | - | 12.6 | 4.0 | 26.3 | | | |

At each visit, participants were assessed and categorized into one of four cognitive statuses: Normal Cognition (NC), Mild Cognitive Impairment (MCI), Dementia (Dem), or Cognitive Impairment not MCI (CI), based on clinical diagnoses.

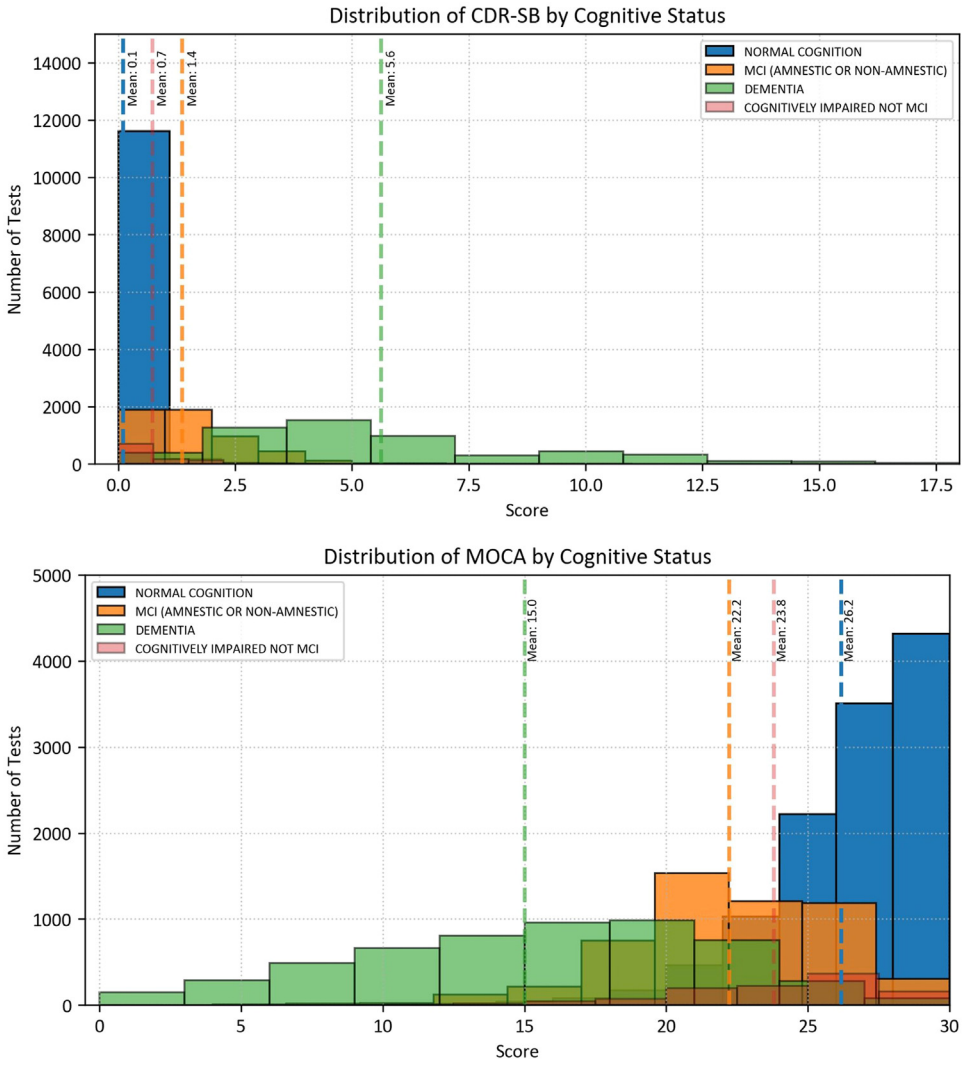


**Fig. 1.** Frequency distribution of observed MoCA and CDR-SB test values from patients' first visits in the full crosswalk cohort.

same day. A total of 23,717 unique patients met the inclusion criteria, contributing 59,871 recorded visits. The cohort was stratified based on cognitive status at the first recorded visit: normal cognition (NC; $n$ = 11,846), mild cognitive impairment (MCI; $n$ = 5349), dementia (Dem; $n$ = 5438), and cognitively impaired but not MCI (CI [Not MCI]; $n$ = 1084). The number of visits per patient ranged from 1 to 10, with approximately 40 % of patients having only one visit, reflecting differences in follow-up duration and retention within the registry.

Table 1 summarizes the demographic and clinical characteristics of the study cohort at their initial visit. The mean age was 69.4 to 72.1 years across patient populations. The proportion of females was highest in the NC group (65.2 %) and decreased progressively across MCI (49.6 %), dementia (48.5 %), and CI [Not MCI] (59.5 %). The cohort was predominantly White (66.1 % to 87.2 %), followed by Black (7.6 % to 27.1 %), with other racial groups comprising smaller proportions. APOE genotyping was available for a subset of participants, revealing that most individuals were non-carriers of the APOE $\varepsilon$4 allele. Among those carrying the $\varepsilon$4 allele, heterozygous carriers outnumbered homozygous carriers, reflecting expected population distributions related to genetic risk factors for AD.

CDR-SB scores spanned a broad spectrum, ranging from no impairment among those with normal cognition to high levels of cognitive and functional impairment among those with dementia. MoCA scores exhibited a similar pattern, with higher scores generally observed in those with normal cognition and lower scores in individuals with dementia.

Alzheimer's disease was the primary etiologic diagnosis, accounting for more than half of cases in the MCI and dementia groups. Table 1 also provides a detailed overview of patients with AD as their primary etiologic diagnosis, with demographic information derived from their initial visit. This subgroup, referred to as the AD cohort, included participants diagnosed with either MCI due to AD or dementia due to AD, excluding those with mixed etiologies. Compared to the broader sample, this cohort tends to be slightly older, with a mean age ranging from 72.7 to 75.2 years across cognitive categories and includes a higher proportion of female participants. There is also a notably greater prevalence of APOE $\varepsilon$4 carriers, reflecting the well-established genetic association with AD. The AD cohort was specifically used to examine the crosswalk between the CDR-SB and MoCA within the context of an Alzheimer's diagnosis. Lewy body disease, frontotemporal disorders, and vascular dementia were also present, though at lower frequencies. Some cases of cognitive impairment were attributed to non-neurodegenerative causes, including traumatic brain injury and systemic illnesses.

### 3.2. Correlation between CDR-SB and MoCA

The distribution of test scores across clinically diagnosed cognitive categories is illustrated in Fig. 1. For the CDR-SB, mean scores progressively increase with advancing cognitive impairment, ranging from normal cognition to dementia, reflecting greater functional and cognitive decline. In contrast, mean MoCA scores decrease as cognitive im-

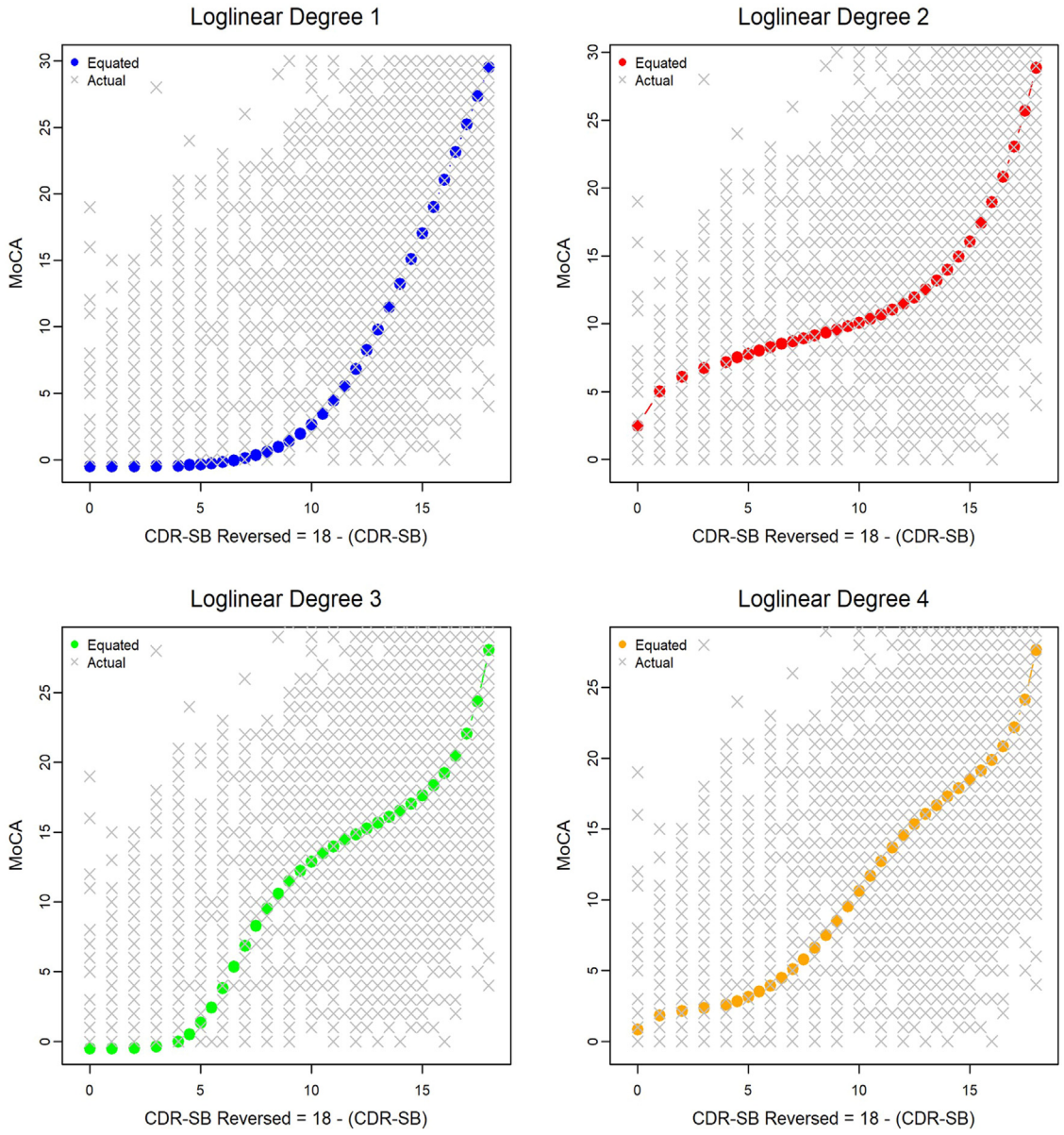


**Fig. 2.** Equating models for CDR-SB to MoCA conversion using log-linear smoothing across degrees ($d$ = 1, 2, 3, and 4).

pairment worsens, consistent with the MoCA's scoring direction, where lower scores indicate more severe cognitive dysfunction. As shown in Fig. 1, CDR-SB scores demonstrate lower overlap across cognitive statuses compared to MoCA, suggesting that CDR-SB may provide a more distinct separation between different levels of cognitive impairment. This clearer differentiation highlights its utility in distinguishing between cognitive stages within the AD cohort.

The Spearman rank correlation coefficient between MoCA and CDR-SB is −0.68 ($p < 0.001$), indicating a strong and statistically significant negative correlation between the two measures, as expected given their inverse relationship in assessing cognitive function.

### 3.3. Score conversion

This study successfully developed a robust conversion framework between CDR-SB and MoCA scores, enabling seamless interoperability between these widely used cognitive assessment tools. The conversion model was built on an equipercentile equating approach, which aligns score distributions by matching percentile ranks, thereby allowing for direct translation between the two measures.

To address sparse score frequencies and improve the overall stability of the transformation process, log-linear smoothing was applied to the score distributions. The optimal degree of smoothing was determined by systematically evaluating polynomial degrees (ranging from 1 to 10) using established criteria such as MSE, AIC, and BIC. The dataset was partitioned into training and test sets to validate the models and ensure their generalizability. For the full cohort, a log-linear smoothing degree of 4 provided optimal performance for converting scores in both directions. In contrast, within the AD cohort, a smoothing degree of 2 was optimal for the CDR-SB to MoCA conversion, while a degree of 3 yielded the best results for converting MoCA to CDR-SB. This divergence highlights the importance of tailoring smoothing parameters to the clinical characteristics of specific subgroups, ensuring more precise and context-specific score equating in a homogeneous population.

Model performance varied across the cognitive spectrum as illustrated in Fig. 2. Lower smoothing degrees, such as degree 1, performed adequately for cases at the extremes—normal cognition and severe de-

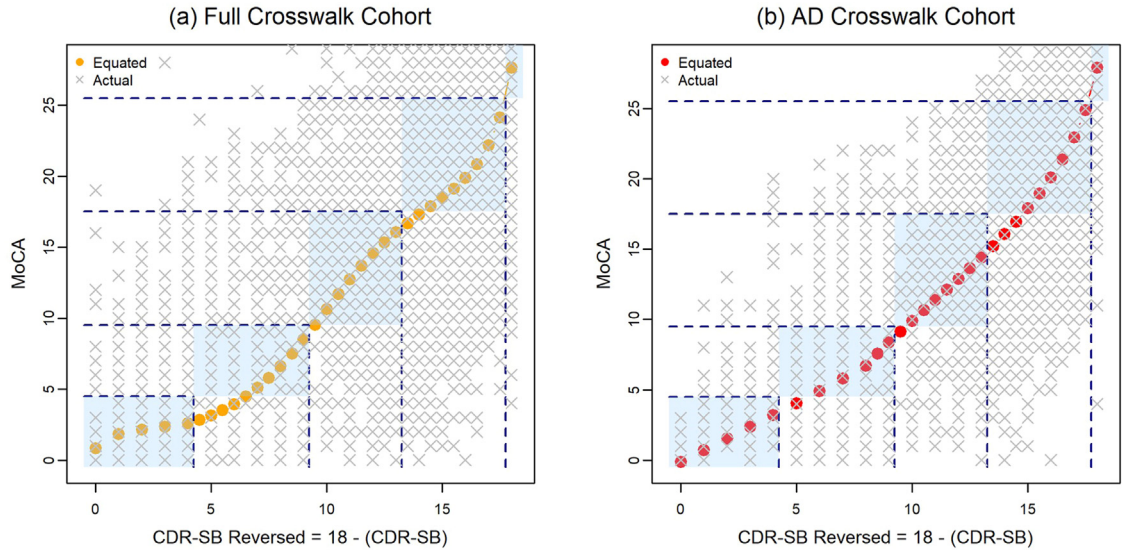


**Fig. 3.** The figures present the equated models and optimal conversion ranges across various cognitive statuses. Fig. 4(a) depicts the full cohort analysis, applying an equated conversion model with a log-linear smoothing degree of 4, while Fig. 4(b) highlights the AD cohort analysis, using a log-linear smoothing degree of 2.

mentia—but were less effective in distinguishing intermediate levels of impairment. In contrast, higher smoothing degrees, particularly degree 4, significantly enhanced the model's sensitivity in differentiating subtle transitions in cognitive status, such as distinguishing MCI from mild dementia and mild from moderate dementia.

Scatter plots of CDR-SB versus MoCA scores (Fig. 3) demonstrated that the equated models aligned closely with clinically established cognitive thresholds. In this context, CDR-SB score cutoffs for disease staging in our study participants were: 0–0.5 for normal cognition, 0.5–4.0 for MCI, 4.5–9.0 for mild dementia, 9.5–14.0 for moderate dementia, and ≥14.0 for severe dementia. Correspondingly, MoCA scores of 26–30 indicate normal cognition, 18–25 represent MCI, 10–17 correspond to mild dementia, 5–9 denote moderate dementia, and 0–4 reflect severe dementia.

While the full cohort conversion model with a log-linear smoothing degree of 4 provided accurate estimates across most cognitive statuses, some overlap occurred between moderate and severe dementia categories. Notably, the AD cohort model—optimized with a smoothing degree of 2—exhibited superior performance in capturing transitions within the severe dementia range, offering more precise differentiation at the advanced stages of cognitive impairment.

After smoothing the score distributions for both the CDR-SB and MoCA assessments, their CDFs were successfully aligned. This alignment process allowed for the direct mapping of scores between the two scales based on corresponding percentile ranks within their respective populations. As shown in Fig. 4, the aligned CDFs demonstrated a consistent relationship between CDR-SB and MoCA scores across the full range of observed values. Lower CDR-SB scores (indicating better cognitive status) corresponded with higher MoCA scores, as expected. The percentile-based mapping preserved the relative ranking of individuals, ensuring that a given percentile on one assessment reliably reflected the equivalent percentile on the other. This consistent correspondence confirms the validity of using aligned CDFs for crosswalk conversions between these two commonly used cognitive assessments in AD research.

Fig. 5(a) presents the Bland-Altman plot for the conversion of CDR-SB scores to MoCA scores in the Full crosswalk cohort. The plot demonstrates a 94.1 % agreement, indicating strong overall concordance between the raw and converted scores across the range of values. Similarly, Fig. 5(b) displays the corresponding plot for the AD crosswalk cohort, with an even higher agreement of 95.5 %. To better visualize the distribution and concentration of data points, a kernel density estimation (KDE) overlay was applied to both plots. This density overlay helps identify areas where data points cluster more densely, offering additional insight into where the linking function performs most consistently or where potential variability may exist.

Robust conversion tables were derived from 1000 bootstrap iterations to ensure reliability and precision, with 95 % confidence intervals (CIs) calculated based on the bootstrap distributions. These bidirectional tables, presented separately for the full cohort and the AD cohort (Table 2), round MoCA scores to the nearest integer and CDR-SB scores to the nearest half-point. For instance, a MoCA score of 28 consistently corresponds to a CDR-SB score of 0 across both cohorts, reinforcing its utility as a marker of normal cognitive function. The conversion tables also revealed that scores at the extremes of the cognitive spectrum exhibit narrower 95 % confidence intervals compared to those in the intermediate range, indicating greater precision in these domains.

Clinically, the cohort-specific conversion tables offer targeted utility: the full cohort conversion is best suited for tracking transitions from normal cognition to MCI or mild dementia, while the AD cohort conversion provides enhanced accuracy for monitoring progression within severe dementia stages. Given the imbalanced composition of the dataset—with a predominance of normal and MCI cases—the focused analysis of the AD cohort yielded more precise conversions for patients with established Alzheimer's dementia.

## 4. Discussion

The conversion framework developed in this study leverages equipercentile equating—a rigorous, nonparametric statistical method—to create a bidirectional crosswalk between CDR-SB and MoCA scores. By aligning percentile ranks across these two widely used instruments, our approach enables scores from one assessment to be translated into equivalent scores on the other, thereby facilitating more consistent disease monitoring, therapeutic decision-making, and comparability of findings across diverse research and clinical practice settings in AD. Previous studies have linked MoCA to MMSE [17,24,25] and CDR to MMSE [26,27]. To our knowledge, this is the first direct equipercentile crosswalk between CDR-SB and MoCA, extending prior work by enabling translation between cognitive and cognitive-plus-functional assessments, and offering a pragmatic tool for harmonizing trial endpoints and observational cohorts. This framework was validated through comprehensive model optimization and agreement analyses,

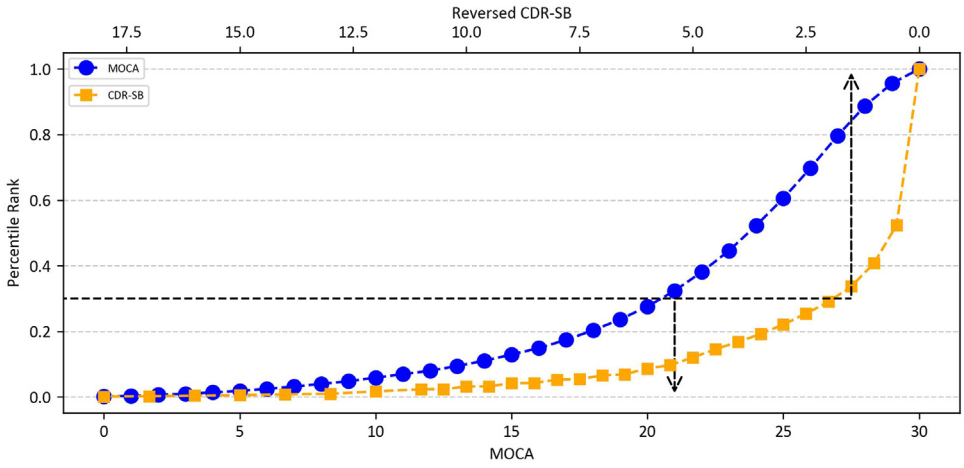


**Fig. 4.** shows the equipercentile equivalent scores on the MoCA and CDR-SB scales, along with their corresponding percentile ranks. The dashed lines indicate points where MoCA and CDR-SB scores are considered equivalent, based on matching percentile ranks.

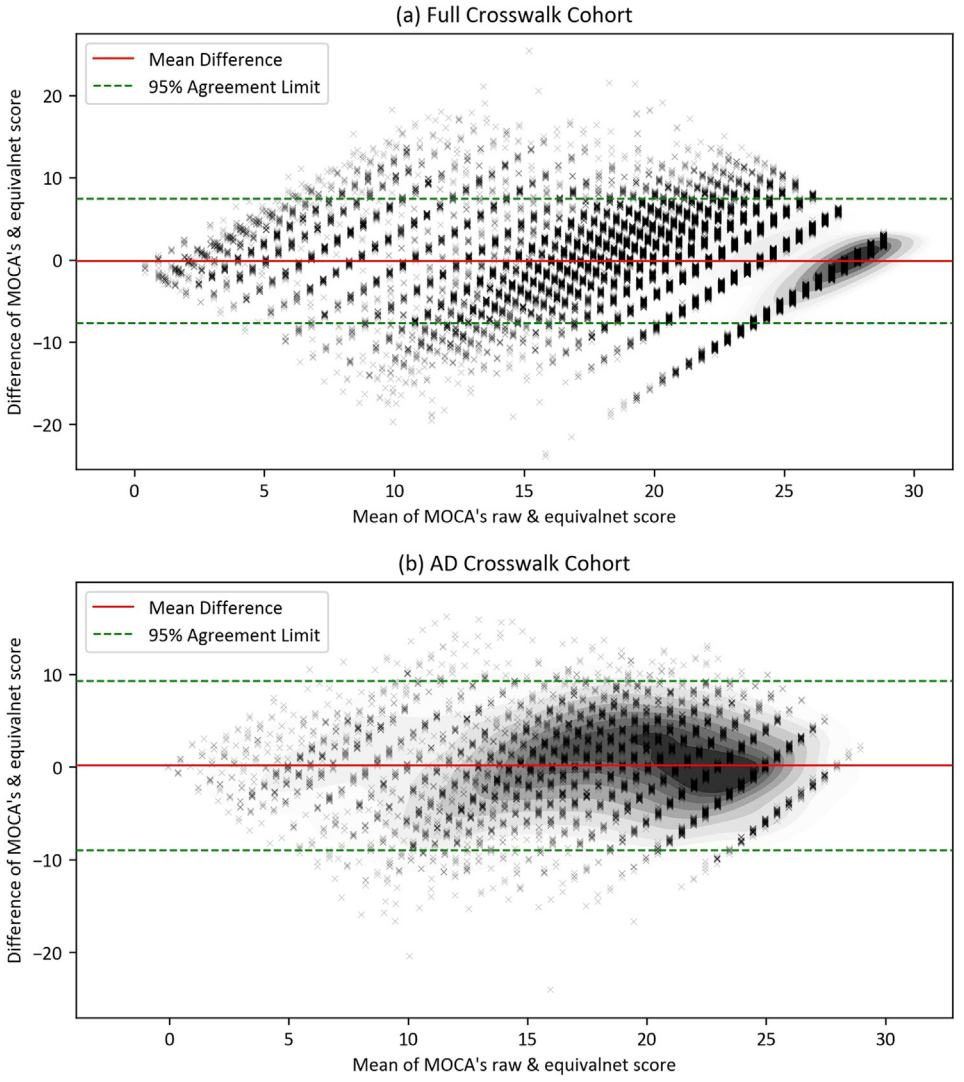


**Fig. 5.** Bland-Altman plots illustrating the conversion of CDR-SB to MoCA scores are presented for the Full crosswalk cohort (a), demonstrating a 94.1 % agreement, and for the AD crosswalk cohort (b), showing a 95.5 % agreement. To enhance visualization of the distribution and clustering of data points, a kernel density estimation (KDE) overlay was applied to both plots.

supporting its utility for data harmonization in large, heterogeneous cohorts. Additionally, confidence intervals for each mapped score are reported in the crosswalk tables (Table 2), providing a quantitative measure of statistical uncertainty. Notably, these intervals are found to be consistent across the score range, including the mid-range where clinical thresholds for MCI and dementia are typically defined. This reflects the robustness of our equating methodology and the large, heterogeneous sample from which the crosswalk was derived. As a result, statistical precision is maintained across the cognitive spectrum.

While equipercentile equating aligns the score distributions of two measures, it does not imply that the underlying constructs are fully interchangeable. The CDR-SB encompasses both cognitive and functional do-

**Table 2**
Crosswalk reference: CDR-SB and MoCA score conversion tables.

| | Full Crosswalk Cohort ($N$ = 59,871) | | AD Crosswalk Cohort ($N$ = 7121) | | | Full Crosswalk Cohort ($N$ = 59,871) | | AD Crosswalk Cohort ($N$ = 7121) | |
|---|---|---|---|---|---|---|---|---|---|
| **CDR-SB** | Eq. MoCA | 95 % CI | Eq. MoCA | 95 % CI | **MoCA** | Eq. CDR-SB | 95 % CI | Eq. CDR-SB | 95 % CI |
| 0 | 28 | [28–28] | 28 | [28–28] | 0 | 18.0 | [18–18] | 17.0 | [16.5–18] |
| 0.5 | 24 | [24–24] | 25 | [25–25] | 1 | 18.0 | [17.5–18] | 15.0 | [14–16] |
| 1.0 | 22 | [22–22] | 23 | [23–23] | 2 | 16.5 | [15–18] | 13.0 | [12–14] |
| 1.5 | 21 | [21–21] | 21 | [21–22] | 3 | 13.0 | [12–14] | 12.0 | [11–13] |
| 2.0 | 20 | [20–20] | 20 | [20–20] | 4 | 12.0 | [11–12.5] | 11.0 | [10–11.5] |
| 2.5 | 19 | [19–19] | 19 | [19–19] | 5 | 11.0 | [10.5–11.5] | 10.0 | [9.5–10.5] |
| 3.0 | 19 | [18–19] | 18 | [18–18] | 6 | 10.5 | [10–10.5] | 9.5 | [8.5–10] |
| 3.5 | 18 | [18–18] | 17 | [17–17] | 7 | 9.5 | [9.5–10] | 8.5 | [8–9.5] |
| 4.0 | 17 | [17–18] | 16 | [16–16] | 8 | 9.0 | [9–9.5] | 8.5 | [7.5–9] |
| 4.5 | 17 | [16–17] | 15 | [15–16] | 9 | 8.5 | [8.5–9] | 8.0 | [7.5–8.5] |
| 5.0 | 16 | [16–16] | 14 | [14–15] | 10 | 8.0 | [8–8.5] | 7.5 | [7–8] |
| 5.5 | 15 | [15–16] | 14 | [13–14] | 11 | 8.0 | [7.5–8] | 7.0 | [6.5–7.5] |
| 6.0 | 15 | [14–15] | 13 | [12–13] | 12 | 7.5 | [7–7.5] | 6.5 | [6–7] |
| 6.5 | 14 | [13–14] | 12 | [12–12] | 13 | 7.0 | [6.5–7] | 6.0 | [5.5–6.5] |
| 7.0 | 13 | [12–13] | 11 | [11–12] | 14 | 6.5 | [6–6.5] | 5.5 | [5–6] |
| 7.5 | 12 | [11–12] | 10 | [10–11] | 15 | 5.5 | [5.5–6] | 5.0 | [4.5–5.5] |
| 8.0 | 11 | [10–11] | 9 | [9–10] | 16 | 5.0 | [4.5–5.5] | 4.5 | [4–5] |
| 8.5 | 9 | [9–10] | 9 | [8–9] | 17 | 4.0 | [4–4.5] | 4.0 | [3.5–4] |
| 9.0 | 8 | [8–9] | 8 | [7–8] | 18 | 3.5 | [3–4] | 3.5 | [3–3.5] |
| 9.5 | 7 | [7–8] | 8 | [7–8] | 19 | 2.5 | [2.5–3] | 3.0 | [2.5–3] |
| 10.0 | 6 | [6–7] | 7 | [6–7] | 20 | 2.0 | [1.5–2] | 2.5 | [2–2.5] |
| 10.5 | 6 | [5–6] | 7 | [6–7] | 21 | 1.5 | [1.5–1.5] | 2.0 | [1.5–2] |
| 11.0 | 5 | [5–5] | 6 | [5–6] | 22 | 1.0 | [1–1] | 1.5 | [1–1.5] |
| 11.5 | 4 | [4–5] | 6 | [5–6] | 23 | 0.5 | [0.5–1] | 1.0 | [1–1] |
| 12.0 | 4 | [4–4] | 5 | [4–6] | 24 | 0.5 | [0.5–0.5] | 0.5 | [0.5–1] |
| 12.5 | 3 | [3–4] | 5 | [4–6] | 25 | 0.5 | [0.5–0.5] | 0.5 | [0–0.5] |
| 13.0 | 3 | [3–3] | 4 | [3–5] | 26 | 0 | [0–0] | 0 | [0–0.5] |
| 13.5 | 3 | [2–3] | 4 | [3–5] | 27 | 0 | [0–0] | 0 | [0–0] |
| 14.0 | 3 | [2–3] | 3 | [2–4] | 28 | 0 | [0–0] | 0 | [0–0] |
| 15.0 | 2 | [2–3] | 2 | [1–3] | 29 | 0 | [0–0] | 0 | [0–0] |
| 16.0 | 2 | [2–2] | 2 | [1–2] | 30 | 0 | [0–0] | 0 | [0–0] |
| 17.0 | 2 | [1–2] | 1 | [0–1] | | | | | |
| 18.0 | 1 | [0–1] | 0 | [0–0] | | | | | |

Clinical Dementia Rating – Sum of Boxes (CDR-SB), Montreal Cognitive Assessment (MoCA).

mains, capturing real-world abilities such as managing personal care and participating in community activities. In contrast, the MoCA is a brief cognitive screening tool that does not assess functional status and may be influenced by educational and cultural factors. As such, scores derived through statistical mapping reflect distributional correspondence rather than conceptual equivalence and should be interpreted with caution, particularly when cognitive and functional outcomes may follow different trajectories [12,28–30].

Previous studies, including those conducted by the NACC, have demonstrated the reliability of equipercentile equating in maintaining continuity between new and existing cognitive assessments [17,22,24,25]. Consistent with these findings, our study confirms the utility of this approach for equating CDR-SB and MoCA scores.

The robustness of the NACC dataset further strengthens the validity of our findings. This dataset is characterized by comprehensive and standardized data collection, which has previously enabled successful equating between various cognitive measures. For instance, the NACC Crosswalk Study effectively utilized equipercentile equating to develop accurate conversion tables between new and legacy cognitive assessments [22]. Our study extends these efforts by providing a new conversion framework specifically linking CDR-SB and MoCA scores, facilitating more accurate data integration and interpretation across clinical and research contexts.

To enhance the accuracy and stability of the equating process, we applied log-linear smoothing to the score distributions. Smoothing parameters were optimized by evaluating polynomial degrees (ranging from 1 to 10) and selecting the degree that minimized MSE, AIC, and BIC on a holdout validation set. This approach, previously used in dementia scale harmonization studies [17,24,25], helped reduce overfitting and preserved key distributional characteristics across subgroups with differing etiologies and disease stages, thereby supporting the generalizability of our findings. For the full study participants, a smoothing degree of 4 provided the best overall performance. In contrast, the AD cohort demonstrated superior accuracy with a smoothing degree of 2 for CDR-SB to MoCA conversion and a degree of 3 for the reverse. This tailored approach underscores the importance of cohort-specific adjustments to optimize precision in different clinical contexts.

The model's performance varied across the cognitive spectrum, with the degree of log-linear smoothing applied during equating playing a critical role in the accuracy and interpretability of the crosswalk. Lower smoothing degrees (e.g., degree 1) performed adequately at the extremes of cognition—normal function and severe dementia—where score distributions exhibit less variability and clinical profiles are more clearly defined, reflecting relatively homogeneous biological states. However, these lower degrees were limited in distinguishing intermediate levels of impairment due to overlapping score distributions and measurement noise inherent to polytomous cognitive assessments. In contrast, higher smoothing degrees, particularly degree 4, enhanced the model's sensitivity in capturing subtle cognitive transitions, such as distinguishing MCI from mild dementia or mild from moderate dementia, by reducing sampling variability while preserving clinically meaningful trends. These findings align with prior research demonstrating greater precision at the extremes of the cognitive continuum in MMSE-MoCA conversions, where clearly defined clinical profiles and reduced floor/ceiling effects simplify equating [24]. It may also reflect overlapping etiologies and variable progression that contribute to score variability. Importantly, improved precision in the mid-spectrum is particularly relevant for early diagnosis and for accurately identifying patients

eligible for clinical trials or disease-modifying therapies, where distinguishing between MCI and early dementia is critical for optimal patient care and research outcomes.

A major strength of our study is the development of separate conversion tables for the AD cohort. This distinction reflects the heterogeneity of cognitive impairment and the influence of underlying pathologies on cognitive trajectories. The full cohort conversion is well-suited for monitoring transitions from normal cognition to MCI or mild dementia, while the AD cohort conversion provides superior accuracy for assessing disease progression within established AD dementia stages. This nuanced approach enhances the clinical utility of the framework, allowing for more precise monitoring across the AD continuum.

Clinically, this conversion framework enables seamless integration of CDR-SB and MoCA assessments, supporting longitudinal monitoring even when different cognitive tools are used across timepoints. This is particularly valuable in multi-center studies and real-world clinical practice, where assessment protocols often vary. Given the widespread use of MoCA in routine clinical evaluations, the derived conversion tables serve as a critical bridge between clinical research and everyday practice, facilitating the interpretation of cognitive and functional changes across diverse settings. This interoperability not only enhances comprehensive patient evaluation—offering clinicians a more holistic understanding of disease progression—but also informs policy decisions and reimbursement strategies. By providing a standardized method to translate between these measures, the framework supports evidence-based decision-making in real-world contexts, improving alignment between clinical outcomes and healthcare policy.

From a research perspective, the developed conversion tables facilitate data harmonization across studies utilizing different cognitive assessments. This improves statistical power, supports meta-analyses, and enhances collaborative efforts across diverse research initiatives. By providing empirically derived, bidirectional conversions, this framework addresses a critical gap in AD research, fostering greater comparability and reproducibility of findings.

Despite these strengths, several limitations warrant consideration. First, while our crosswalk demonstrates strong statistical precision across the cognitive spectrum, it is anchored to clinical diagnoses rather than a biomarker- or pathology-based gold standard. Because CDR-SB and MoCA thresholds are not perfectly aligned with each other or with underlying disease biology, mapped scores—especially near diagnostic cutoffs—should be interpreted within a broader clinical context. Validation in biomarker-defined cohorts is needed to confirm the extent to which equated scores reflect true disease stage. Second, the conversions were derived from a specific patient cohort, necessitating further validation in more diverse populations with varying demographic and clinical characteristics. While our cross-sectional approach provides a robust snapshot of cognitive equivalence, future studies incorporating longitudinal data are needed to assess the stability of these conversions over time. Third, fundamental differences between the CDR-SB and MoCA may impact the generalizability of our crosswalk. The CDR-SB assesses both cognitive and functional domains, including personal care and community activities, capturing real-world impairment that is not assessed by the MoCA. This distinction may limit the utility of the crosswalk in cases of isolated cognitive disorders without significant functional decline [28,29]. Conversely, MoCA performance is sensitive to education level and cultural background, which can lead to underestimation of impairment in individuals with lower educational attainment. The semi-structured, informant-based format of the CDR may help mitigate the confounding effects of educational background [12,30]. Finally, extending this framework to additional cognitive and functional measures may support the development of a more comprehensive toolkit for assessing and monitoring AD progression.

In conclusion, this study presents a rigorously validated, bidirectional conversion framework between CDR-SB and MoCA scores, providing a practical solution for integrating cognitive and/or functional data across clinical and research settings. By enhancing the interoperability of these widely used assessments, the framework promotes more consistent disease monitoring, facilitates data harmonization, and may help inform clinical and reimbursement decisions. These conversion tables are intended to serve as a supportive tool and should be interpreted within the broader clinical context, ideally in conjunction with additional clinical information and, where available, biomarker data. Further validation in biomarker-defined cohorts will be valuable to confirm their clinical relevance and to refine their application. As the field advances, such conversion tools will play a crucial role in improving diagnostic accuracy, optimizing patient care, and accelerating research in AD and related dementias.

## Medical writing, editorial, and other assistance

All authors contributed to the work, and no medical writing, editorial, or other assistance was provided.

## Ethics/Ethical approval

All contributing ADRCs are required to obtain informed consent from participants and secure independent Institutional Review Board (IRB) approvals from their respective institutions prior to submitting data to NACC. The study was conducted in accordance with the ethical standards outlined in the 1964 Declaration of Helsinki and its subsequent amendments, or other comparable ethical guidelines. This study does not involve any new research with human participants or animals conducted by the authors.

## Prior publication

This is original work and has not been previously published or submitted elsewhere.

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## Data availability

All NACC data is freely available to researchers at https://naccdata.org/.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Drs. Haji and Zhang are employees of Eisai Inc. Dr. Tahami Monfared is also an employee of Eisai Inc. and holds the position of Adjunct Professor in the Department of Epidemiology, Biostatistics, and Occupational Health at McGill University. Additionally, he serves as an Associate Editor for the *Journal of Alzheimer's Disease*, for which he receives no honorarium. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## CRediT authorship contribution statement

**Babak Haji:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Quanwu Zhang:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization. **Amir Abbas Tahami Monfared:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

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