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Article

Psychometric Properties of the Montreal Cognitive Assessment (MoCA) in Spanish Adults

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ABSTRACT

Background: The Montreal Cognitive Assessment (MoCA) is widely used for cognitive screening, but its dimensionality and domain-specific accuracy require validation with methods for ordinal items. The objective was to analyze the internal structure of the MoCA in a cognitive impairment-free Spanish community sample and examine its relationship with variables potentially related to the risk of cognitive impairment. **Method:** A total of 1,767 Spanish adults (aged 18-89 years) were assessed in primary care centers using the MoCA, and sociodemographic and health variables were recorded. Internal structure and metric properties were analyzed using factor models and item response theory, as well as their association with external variables and the concordance of the resulting solution. **Results:** The theoretical models tested did not demonstrate adequate fit. Cross-validation identified a 12-item solution in two correlated factors (Memory and Multiple), with excellent fit (CFI = .991; RMSEA = .019) and latent correlation r = .63. The abbreviated version showed high concordance with the total score (ICC = .96) and substantial agreement in dichotomous classification (k = .84). **Conclusions:** The MoCA exhibited a two-factor structure and consistent associations with external variables such as age, educational level, and vascular risk; a dimensional interpretation is recommended.

Propiedades Psicométricas del Montreal Cognitive Assessment (MoCA) en Adultos Españoles

Palabras clave:
Validez de constructo
MIRT
Rastreo cognitivo
Psicometría

RESUMEN

Antecedentes: El Montreal Cognitive Assessment (MoCA) se emplea ampliamente para el rastreo cognitivo, pero su dimensionalidad y precisión por dominio requieren validación con métodos para ítems ordinales. El objetivo fue analizar la estructura interna del MoCA en una muestra comunitaria española sin deterioro cognitivo (DC) y examinar su relación con variables potencialmente relacionadas con el riesgo de DC. **Método:** Se evaluó a 1,767 adultos (18-89 años) españoles procedentes de centros de atención primaria mediante el MoCA y se registraron variables sociodemográficas y de salud. Se analizaron la estructura interna y propiedades métricas mediante modelos factoriales y teoría de respuesta al ítem, así como su asociación con variables externas y la concordancia de la solución resultante. **Resultados:** Los modelos teóricos contrastados no mostraron ajuste adecuado. La validación cruzada identificó una solución de 12 ítems en dos factores correlacionados (Mnésico y Múltiple), con ajuste excelente (CFI = .991; RMSEA = .019) y correlación latente r = .63. La versión abreviada mostró alta concordancia con la puntuación total (CCI = .96) y acuerdo sustancial en la clasificación dicotómica (k = .84). **Conclusiones:** El MoCA mostró una estructura de dos factores y asociaciones coherentes con variables externas como la edad, el nivel educativo y el riesgo vascular; se recomienda priorizar una interpretación dimensional.

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Cognitive screening instruments enable quick, cost-effective assessments in the general population and facilitate referral to more comprehensive neuropsychological evaluations when appropriate (Chithiramohan et al., 2024). Their usefulness, however, depends on robust psychometric evidence to support structural validity and proper item functioning (Mokkink et al., 2024; Wen et al., 2025).

Since its introduction, and especially in the last decade, the Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005) has become established as a widely used test in screening for mild cognitive impairment (MCI) (O'Caoimh et al., 2025; Wen et al., 2025). Recent meta-analyses support its diagnostic accuracy (with cut-off points between < 23 and < 25 maximizing the sensitivity-specificity balance) and suggest greater sensitivity than the Mini-Mental State Examination (MMSE) in detecting MCI (Ciesielska et al., 2016; Islam et al., 2023). It is organized into seven domains, and while this guides practice, it does not in itself guarantee dimensional validity and requires empirical verification with appropriate methods (Sala et al., 2020; Wen et al., 2025). Although the MoCA was originally designed to sample multiple cognitive domains, it remains unclear whether its items primarily reflect a single general cognitive factor, multiple correlated dimensions, or a hierarchical structure, as prior research has reported inconsistent latent solutions across populations and analytic approaches (Sergi et al., 2025). Structural validity studies in community populations in Portugal (Duro et al., 2010; Freitas et al., 2012, 2015), Ireland (Coen et al., 2016), Chile (Cancino et al., 2020) and China (Luo et al., 2022) have, for example, reported divergent solutions ranging from six-factor models and hierarchical structures to more parsimonious models, thereby reinforcing the need to verify dimensionality in each population. Most of these studies have approached the question from the perspective of classical test theory (CTT) using confirmatory factor analysis (CFA) within the framework of structural equation modelling (SEM) (e.g., Coen et al., 2016; Duro et al., 2010; Freitas et al., 2012). While this is a valuable approach, it does not provide information on item-by-item performance or conditional accuracy across the latent trait (θ). At the same time, studies based on item response theory (IRT) have characterized MoCA at the item level, quantifying discrimination and information across θ and, therefore, conditional accuracy (Embretson & Reise, 2013). Rasch analysis (partial credit model [PCM]) and IRT models for ordinal items (graded response model [GRM]) present information profiles differentiated by domain: memory items and some executive function items provide greater discrimination and information, while orientation and naming items show a ceiling effect, supporting the use of multidimensional approaches (Aiello et al., 2022; Freitas et al., 2015; Tsai et al., 2012). A recent review reports substantial cross-population heterogeneity in MoCA factor solutions and item functioning (Sergi et al., 2025). Accordingly, its dimensional structure should be empirically verified in each population in which it is applied.

In Spain, the MoCA has shown adequate reliability (Pereiro et al., 2017), high test-retest stability (Lozano Gallego et al., 2009) and good-to-excellent inter- and intra-rater agreement (Porto, 2015), as well as satisfactory convergent validity (Pereiro et al, 2015, 2017; Vallés-Salgado et al., 2024) and criterion validity (Lozano Gallego et al., 2009; Matías-Guiu et al., 2017; Ramírez-Moreno et al., 2022; Vallés-Salgado et al., 2024), including community-based normative data (Ojeda et al., 2016; Pereiro et al., 2017) and recent clinical evidence on diagnostic performance in memory-clinic settings (Vallés-Salgado et al., 2024). However, evidence remains comparatively limited for structural validity in large community samples spanning a broad adult age range, particularly using methods appropriate for ordinal items and complemented with item-level modeling to document conditional measurement precision (Bugallo-Carrera et al., 2024; Vallés-Salgado et al., 2024). Consistent with best-practice test-validation frameworks, defensible score use requires evidence of a replicable dimensional structure and appropriate item functioning across key subgroups; thus, beyond Spanish studies focused on norms and diagnostic accuracy, the present study examines the MoCA's latent structure and conditional precision using modern psychometric approaches in a large, cognitive-impairment–free community dwelling sample (Badham et al., 2025; Ferrando et al., 2025). Likewise, evidence remains scarce on the relationship between MoCA and vascular risk and lifestyle biomarkers with prognostic relevance (e.g., composite indices such as CAIDE or ANU-ADRI), associations which have been found in other populations (Guo et al., 2024; Yin et al., 2024). This evidence is directly relevant for community screening and referral, where decisions depend on measurement precision in the range where early impairment is expected.

In view of the above, this study aimed to validate the MoCA in a large cognitive impairment-free Spanish community dwelling sample (aged 18-89 years) by assessing: (a) its internal structure; (b) its measurement properties by factor; and (c) its relationship with vascular risk indicators and lifestyle, in a framework integrating CTT and IRT.

Method

Participants

The sample comprised 1,767 adults aged 18-89 years (M = 51.5, SD = 16.2), of whom 58.5% were women. Participants were drawn from four independent community-based studies (n = 539, 223, 626, and 379) conducted in primary care settings in Castilla y León (Spain). Inclusion criteria were being 18 years of age or older, having Spanish as a native language, agreeing to participate voluntarily, and providing informed consent. Exclusion criteria included a history or diagnosis of neurological conditions with potential impact on cognition (e.g., dementia, MCI), stroke or traumatic brain injury, systemic diseases with cognitive impact (e.g., diabetes), significant sensory or motor limitations, illiteracy, incomplete MoCA, or prior professional familiarity with MoCA. Detailed sample characteristics are presented in Table 1.

Instruments

Montreal Cognitive Assessment (MoCA)

The MoCA is a cognitive screening test with a maximum score of 30 points that assesses seven domains: visuospatial/executive functions, naming, memory, attention, language, abstraction, and orientation. We administered the official Spanish version 8.1 of the MoCA (Nasreddine et al., 2005). This version has been previously validated linguistically (Acquadro et al., 2012). For an expanded description of the items, domains and score ranges, see Table S1.

Table 1
Demographic Characteristics of the Sample (N = 1,767)

Variable	Levels	Summary
Sociodemographic variables		
Age (years)		54 [39-65]
Sex	Women / Men	1,034 (58.5%) / 733 (41.5%)
Education level	Primary / Secondary / University	290 (16.4%) / 681 (38.5%) / 796 (45.0%)
Employment	Employed/ Unemployed	1,391 (78.7%) / 376 (21.3%)
Occupational field (CNO-11)	Natural Sciences / Art and Culture / Health / Social Sciences and Education / Processing and Manufacturing / Primary Resources / Finance and Administration / Transportation / Sales and Services	465 (33.4%) / 299 (21.5%) / 176 (12.7%) / 165 (11.9%) / 114 (8.2%) / 83 (6.0%) / 56 (4.0%) / 29 (2.1%) / 4 (0.3%)
Level of professional qualifications	A / B / C / D	83 (6.0%) / 452 (32.5%) / 375 (27.0%) / 481 (34.6%)
Clinical variables		
SBP / DBP (mmHg)		124 [112-137] / 78 [71-86]
Hypertension	Yes / No	594 (33.6%) / 1,173 (66.4%)
BMI	Underweight / Normal weight / Overweight / Obesity	29 (1.6%) / 749 (42.4%) / 670 (37.9%) / 319 (18.1%)
BMI (kg/m²)		25.7 [22.9-28.8]
Total cholesterol (mg/dL)		193 [170-218]
HDL / LDL (mg/dL)		57 [49-69] / 114 [94-135]
Triglycerides (mg/dL)		88 [67-120]
Glucose (mg/dL)		86 [80-93]
Antidepressants / Anxiolytics	Use	100 (5.7%) / 122 (6.9%)
Lifestyle		
Alcohol	Non-drinker / Low-risk drinker / At-risk drinker	564 (31.9%) / 945 (53.5%) / 258 (14.6%)
Alcohol (SDU/wk)		2.2 [0.0-6.3]
Physical activity	Low/ Moderate / High	242 (13.7%) / 929 (52.6%) / 596 (33.7%)
Physical activity (MET-min/wk)		2,970 [1,485-4,348]
Variable	**Levels**	**Summary**
Smoking	never smoked / ex-smoker > 5 years / ex-smoker 1-5 years / ex-smoker 0-1 year / yes, regularly	857 (48.5%) / 512 (29.0%) / 75 (4.2%) / 32 (1.8%) / 291 (16.5%)
PYI		13.6 [5.5-28.9]
CAIDE Index		
CAIDE index	Very low risk / Low risk / Moderate risk / High risk / Very high risk	1,073 (60.7%) / 389 (22.0%) / 184 (10.4%) / 114 (6.5%) / 7 (0.4%)

Note. Continuous variables are reported as median [*IQR*]; categorical variables as *n* (%). Rows for Occupational field (CNO-11) and Professional qualification levels were computed within the Employed subgroup (*n* = 1,391). Alcohol categories follow Spain's Ministry of Health thresholds (≤1 SDU/day for women; ≤2 SDU/day for men; reported here as SDU/wk). CNO-11 = Clasificación Nacional de Ocupaciones 2011 [National Classification of Occupations 2011 (CNO-11)]; SBP: systolic blood pressure; DBP: diastolic blood pressure; BMI = body mass index; HDL = high-density lipoprotein; LDL = low-density lipoprotein; MET = metabolic equivalent of task; PYI = pack-year index; CAIDE = Cardiovascular Risk Factors, Aging and Dementia.

Sociodemographic Variables

We recorded age, sex (assigned at birth), educational level, coded according to the Spanish system as illiterate, primary education (≤ 12 years of schooling), secondary education (13–15 years) or university studies (≥ 16 years), employment status, occupational field according to the Clasificación Nacional de Ocupaciones de España (Spanish National Classification of Occupations) (CNO-11) and level of professional qualification (categories A–D) according to the criteria of the Instituto Nacional de Estadística (National Institute of Statistics [INE]) (2011).

Clinical Variables

The use of antidepressants and/or anxiolytics was obtained by interview and verification in medical records. Blood pressure was measured with an OMRON M10-IT sphygmomanometer (Omron Healthcare, Kyoto, Japan) by taking three readings and averaging the last two, on the dominant arm, with the participant seated and after ≥ 5 minutes of rest, according to the European Society of Hypertension recommendations (Williams et al., 2018). Hypertension was defined as systolic blood pressure ≥ 140 mmHg or diastolic blood pressure ≥ 90 mmHg, a prior diagnosis, or antihypertensive treatment.

Body mass index (BMI = kg/m²) was calculated and classified, following WHO criteria, as obese (BMI ≥ 30 kg/m²), overweight (25-29.9 kg/m²), and normal weight (< 25 kg/m²). Fasting blood tests were carried out (total cholesterol, HDL, triglycerides, and glucose), and LDL was estimated with the Friedewald formula.

Lifestyle

Alcohol use was recorded through a structured questionnaire about the quantity and type of alcoholic drinks consumed in the previous seven days, expressed as standard drink units (SDUs) per week (1 SDU = 10 g of pure alcohol). Participants were classified in three categories, following the recommendation of the Spanish Ministry of Health (2020): non-drinker, low-risk drinker, and at-risk drinker. Physical activity was assessed using the short version of the IPAQ (Craig et al., 2003), deriving MET-min/week and the categories low/moderate/high. Smoking status was recorded to calculate the pack-year index (PKI).

CAIDE Index

The cardiovascular risk factors, aging and incidence of dementia (CAIDE) score was estimated as the weighted sum of age, sex, educational level, blood pressure, total cholesterol, BMI, and physical activity. The range is 0-15, and an ordinal classification with five levels—very low risk (0-5), low (6-7), moderate (8-9), high (10-11), and very high (12-15)—was used given its greater informative capacity and clinical utility (Kivipelto et al., 2006; Sindi et al., 2015).

Procedure

A multi-sample, instrumental study based on secondary data analysis was carried out. Data were drawn from four independent primary care–based studies implemented in community primary care settings in Castilla y León (Spain), with in-person assessments conducted under a shared standardized fieldwork framework. Trained professionals administered the MoCA and collected the remaining measures, and data quality was monitored throughout the fieldwork. Data collection occurred between October 2021 and September 2024. The databases of the four studies were integrated into an initial repository (N = 2,255) using variable harmonization and pre-specified cleaning rules. The studies initially contributed n = 610 (Martí-Lluch et al., 2023), 273 (Llamas-Ramos et al., 2024), 965 (Lugones-Sánchez et al., 2023), and 407 (Vicente-Gabriel et al., 2024) participants, respectively. For the present secondary analysis, range, consistency, and plausibility checks were applied, and a fully anonymized analytical dataset including only complete records for the variables used in the analyses was created prior to psychometric modeling. All studies were approved by the corresponding Ethics Committee and complied with the Declaration of Helsinki (World Medical Association, 2025). After cleaning the integrated database, 299 participants were excluded with type 2 diabetes, 23 with stroke prior to the MoCA, one with a neurological disorder, and 165 due to incomplete MoCA, producing a final sample of N = 1,767.

Data Analysis

To characterize the sample, we calculated descriptive statistics, with absolute frequencies and percentages for categorical variables and median and interquartile range (*IQR*) for continuous variables, as indicated by the Shapiro–Wilk test and inspection of histograms and Q–Q plots. Floor and ceiling effects were analyzed for the total MoCA score and for each resulting subscale (defined a priori as ≥20% of observations at the minimum or maximum value, respectively). Internal consistency was estimated using Cronbach's alpha (α) and McDonald's omega (ω) calculated on polychoric matrices; ω was included as a reliability estimate that is less dependent on restrictive assumptions for ordinal items. Hierarchical omega (ωh) was reported only when multidimensional or bifactor representations were evaluated.

Validation of the internal structure was performed in several phases. First, CFA was performed on the entire sample, with five theoretical models contrasted: 1) a unidimensional baseline model; 2) a two-factor correlated model (Verbal Memory and Executive Attention), as proposed by Duro et al. (2010); 3) a six-factor correlated model representing the theoretical domains of the test, following Freitas et al. (2012); 4) a second-order hierarchical model in which a global cognition factor accounts for covariance among first-order domains (Kline, 2023); and 5) a bifactor model with a general factor and domain-specific group factors, included as a diagnostic specification consistent with prior dimensionality evaluations in MoCA research (Luo et al., 2019) and broader structural syntheses (Sergi et al., 2025). The bifactor model was tested to quantify the proportion of common variance attributable to a general factor relative to specific factors and to inform interpretation of the total score and the incremental reliability of subscale scores (Kline, 2023; Luo et al., 2019). All CFAs were estimated for ordinal items using weighted least squares mean and variance adjusted (WLSMV, theta parameterization, χ^2 scaled). The fit was assessed using the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA, 90% CI) and the standardized root mean square residual (SRMR) according to a priori criteria (CFI/TLI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08) (Hu & Bentler, 1999). For bifactor specifications, additional diagnostics were computed, including explained common variance (ECV) and bifactor reliability indices, and local dependence was evaluated using *Q3* statistics.

In addition, we used an exploratory approach with cross-validation. The sample was randomly divided into two equivalent subsamples (exploratory, n = 884; confirmatory, n = 883) using simple random assignment with a fixed seed. Comparability between subsamples was examined with homogeneity checks for age, sex, and educational level (Table S2). In the exploratory subsample, an exploratory factor analysis (EFA) was applied to a polychoric matrix using ULS (minres) and oblimin rotation. The number of factors was determined by parallel analysis (500 replications), and KMO and Bartlett's test of sphericity were reported. Item retention followed prespecified psychometric criteria aimed at obtaining a stable and interpretable solution. Items were retained when they showed salient primary loadings on a single factor and adequate communalities. Items were considered for exclusion when they showed extreme floor or ceiling effects with limited variability, very low communalities, or weak and unstable contributions to the common factor structure. The resulting structure was validated in the confirmatory subsample using CFA, where its fit was compared to an alternative bifactor model.

Following factorial validation, multidimensional item response theory (MIRT) models were fitted, including a bifactor (general and specific factors) to evaluate essential unidimensionality and potential local dependence, and a two-factor correlated model.

Agreement between the full score and the abbreviated version was estimated using the intraclass correlation coefficient (ICC, 95% CI). Dichotomous agreement (normal performance vs. possible cognitive impairment) was assessed using Cohen's κ (95% CI). For the full MoCA, classification was based on the conventional cutoff of a total score < 26 originally proposed by Nasreddine et al. (2005) and widely used in cognitive screening research (e.g., Islam et al., 2023; Tsoi et al., 2017). An equivalent cutoff for the 12-item form was derived using equipercentile linking between the full and short-form scores: the percentile corresponding to the < 26 classification in the full-score distribution was identified, and the short-form integer threshold matching that percentile was selected. The linking function was logit-smoothed, and uncertainty was quantified via bootstrap resampling to obtain confidence intervals. Finally, associations between MIRT-derived latent scores and

sociodemographic, clinical, and lifestyle variables were examined using Spearman correlations. Additionally, a MIMIC-type structural equation model was specified for the two-factor CFA, in which predictors regressed directly on the latent factors. This model was estimated using robust maximum likelihood (MLR), and standardized effects were reported. As an additional analysis, we fitted regressions on the latent scores obtained through EAP.

All analyses were performed in R 4.3.1 (R Core Team, 2023) using *lavaan* (Rossel, 2012) and *semTools* (Jorgensen et al., 2016) for models with ordinal items and *mirt* (Chalmers, 2012) for IRT analyses. The significance level was set at α = .05 (two-tailed). Reproducible code and analysis scripts are available.

Results

Evidence of Validity Based on Internal Structure

None of the five theoretical models tested using CFA met the full set of prespecified fit criteria (CFI/TLI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08). Complete fit indices are provided in Table S3. Parallel analysis suggested up to four factors; however, eigenvalues attenuated sharply after the second factor (F1 = 3.771; F2 = 0.929; F3 = 0.265; F4 = 0.078). In cross-validation, exploratory factor analysis (EFA) of the exploratory subsample (n = 884) identified a 12-item solution grouped into two correlated factors. The first factor, Memory, consists of the five delayed recall items, and the second, the Multiple factor, comprises following items: the category switch, cube copying, clock drawing, naming lion and rhinoceros, subtraction, and train-bicycle similarity. Accordingly, the two-factor solution was retained and explained 41.1% of the common variance (22.5% and 18.6% per factor) (see Tables S4–S6). This structure showed excellent fit in the confirmatory subsample (n = 883): CFI = .991; TLI = .988; RMSEA = .019 [90% CI; .012, .025]; SRMR = .046. A bifactor (general-specific) model did not provide a substantial improvement over the two-factor model (ΔCFI = .005; ΔRMSEA = .005), so the latter was retained for parsimony. Additional bifactor diagnostics suggested only moderate general-factor saturation (ECV = .58; ωh = .54) and limited specific-factor reliability (ωs Memory = .27; ωs Multiple = .39), with no evidence of meaningful local dependence (maximum positive $Q3$ = .029; 0 item pairs with $Q3$ > .20) (see Table S7). The retained structure explained 39.9% of the common variance (item R^2 values are presented in Table S8).

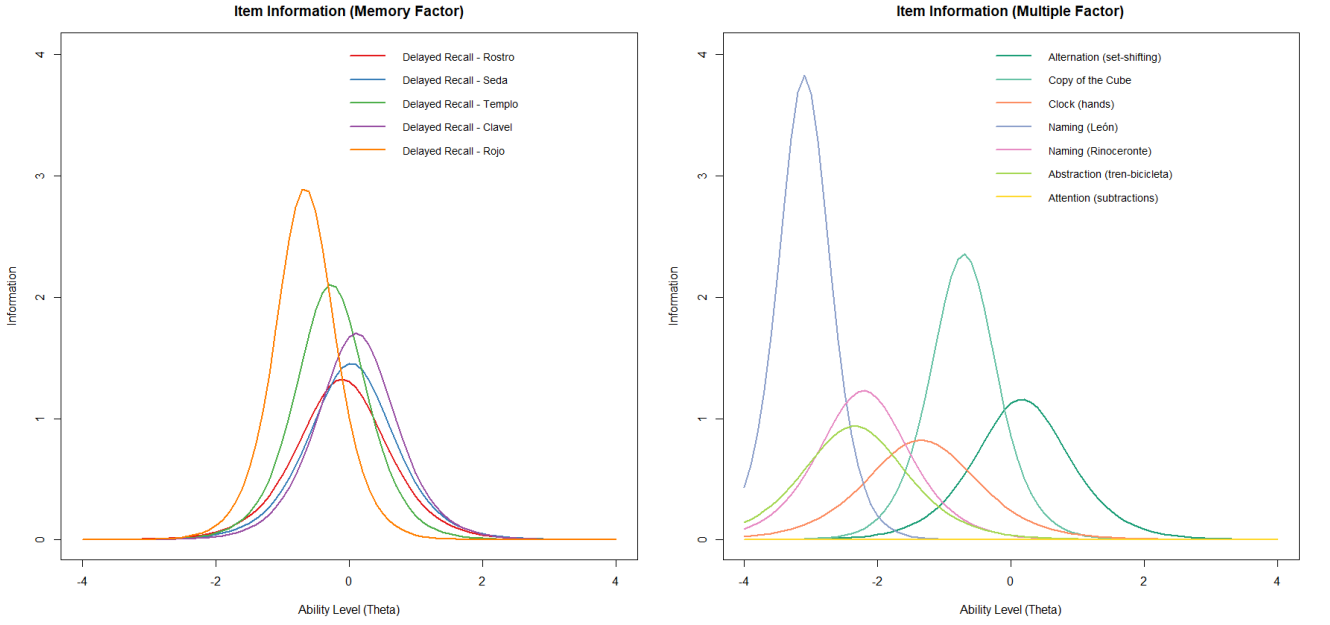
MIRT analyses of the general–specific (bifactor) specification showed estimation anomalies and lack of stable convergence, so this specification was not interpreted further. Instead, the two-correlated-factor model converged to a stable and consistent solution ($M2(_{51})$ = 92.45, p < .001; RMSEA = 0.020 [90% CI; .013, .026]; SRMR = 0.023; CFI = 0.990; TLI = 0.987; AIC = 25431.12; and BIC = 25582.8), with information profiles differentiated by factor and latent correlation r = .625.

The S-X² item fit was acceptable, and there was no relevant local dependence (|$Q3$| > .20) (see Table S7). Discrimination scores ranged from 1.35 to 2.00 for the Memory factor and 1.07 to 2.30 for the Multiple factor (Table S9). The item information curves (IIC) and test information curves (TIC) (Figure 1) showed distinct accuracy profiles: the Multiple factor reached its maximum information (information = 2.606) at a low ability level (θ = -2.9, SEM = 0.619), with information decreasing as θ increased; while the Memory factor reached its maximum (information = 3.071) across a broader ability range (θ = 0.3, SEM = 0.571).

Table 2 summarizes the reliability analysis of the MoCA, its official domains, and final subscales. The mean MoCA score was 24.10 (SD = 3.77; skewness = -0.81). There were marked

Figure 1

Item Information Curves From the Two-Factor MIRT Model



Note: Item Information Curves from the two-factor MIRT model. Memory Factor items peak in the low–mid θ range; Multiple Factor items peak mostly below the mean and lose precision at higher θ.

ceiling effects across several theoretical domains according to the prespecified criterion, including Visuospatial/Executive (29.2%), Naming (90.8%), Attention (46.0%), Language (46.0%), Abstraction (67.8%), and Orientation (93.0%) (see Table S10). No domain-level floor effects reached the prespecified threshold (≥20% at the minimum score). In terms of internal consistency, most domains had $\omega < .60$, with the exception of Delayed Recall ($\omega = .683$). Internal consistency was: ω_total = .717; ω_hierarchical = .613. The Memory factor showed $\omega = .683$ (skewness = -0.26), while the Multiple factor had $\omega = .585$ (skewness = -1.10).

Evidence of Validity Based on Relationships With Other Variables

The Memory factor was moderately associated with age (ρ = -0.46), educational level (ρ = 0.40), and the CAIDE index (ρ = -0.47), and more weakly associated with hypertension (ρ = -0.29) and BMI (ρ = -0.24). The Multiple factor showed moderate correlations with age (ρ = -0.55), educational level (ρ = 0.48), and CAIDE (ρ = -0.48), as well as a significant association with sex (ρ = -0.09) and hypertension (ρ = -0.32). All coefficients reached $p < .001$. The remaining variables showed no or small associations with the latent scores and did not contribute incremental variance to the MIMIC models ($|\rho| < .10$ and/or $q > .05$).

In the adjusted MIMIC model, the explained variance was $R^2 = .378$ for the Memory factor and $R^2 = .545$ for the Multiple factor. The results indicated that age (β = -0.43), education (β = 0.26), sex (β = 0.16), and BMI (β = -0.06) were significant predictors of performance on the Memory factor, while the significant predictors for the Multiple factor were age (β = -0.45), education (β = 0.36), and sex (β = -0.23) (see Table S11).

Finally, the agreement between the total MoCA score and the 12-item reduced version for classifying subjects' cognitive status (normal score or suspected cognitive impairment) was assessed. For continuous scores, the ICC (3, k) was 0.96 (95% CI [.956, .961]). For dichotomous classification (normal performance vs. possible impairment), the short-form cut-off was <11 (Table S12). Categorical agreement was $\kappa = 0.84$ (95% CI [0.819, 0.860]), with 92.2% overall agreement (95% CI [91.1%, 93.1%]). In terms of classification, 764/804 subjects with normal performance and 971/1000 with possible impairment were correctly classified. We found 40 false negatives and 29 false positives.

Discussion

In a large cognitive impairment-free Spanish community dwelling sample (N = 1,767) spanning early adulthood to old age (18-89 years), the MoCA yielded a correlated two-factor solution (Memory and Multiple) comprising 12 items. This study extends previous Spanish validation efforts— which have provided valuable evidence on normative adjustments and screening cut-offs (e.g., Pereiro et al., 2017; Vallés-Salgado et al., 2024)—by providing large-sample evidence on internal structure and item-level measurement precision in a cognitive impairment–free community sample using ordinal modeling, internal cross-validation, and IRT information functions. This solution offers a more parsimonious and interpretable reading of cognitive performance than alternatives based on discrete domains (e.g., Coen et al., 2016; Duro et al., 2010). Given the heterogeneity in MoCA factor solutions and item functioning reported across populations, these results further support the need for population-specific verification and careful score interpretation based on locally supported measurement evidence (Badham et al., 2025; Sergi et al., 2025). The choice of a correlated two-factor model over a general–specific bifactor model is congruent with current recommendations to prioritize simple models with substantive validity and robust empirical performance (Kline, 2023; Marsh et al., 2004; Rodríguez et al., 2016).

From a neuropsychological and neuroscientific perspective, the two-factor solution can be explained by current models of brain and cognitive function based on neural networks (Dragomir & Omurtag, 2021). These models align with the concept of interconnected yet distinct dynamic networks, including the episodic memory network

Table 2
Descriptive and Reliability Analysis of MoCA Items (N = 1,767): Total Scale, Theoretical Domains and Final Subscales

Scale / Domain	No. of Items	Range	Mean (*SD*)	Floor (%)	Ceiling (%)	Cronbach's α	McDonald's ω	Skewness	Kurtosis
MoCA (Total Score)	28	0-30	24.1 (3.77)	0.0%	3.5%	.736	.717	-0.81	0.51
MoCA Domains									
Visuospatial/Executive	5	0-5	3.73 (1.2)	0.3%	29.2%	.450	.434	-0.70	-0.11
Naming	3	0-3	2.90 (0.4)	0.2%	90.8%	.570	.575	-3.87	17.42
Attention	4	0-6	5.04 (1.1)	0.1%	46.0%	.510	.387	-1.41	1.63
Language	3	0-3	2.26 (0.8)	2.8%	46.0%	.410	.344	-0.83	-0.06
Abstraction	2	0-2	1.63 (0.6)	5.1%	67.8%	.460	NE	-1.29	0.65
Delayed Recall	5	0-5	2.90 (1.6)	11.0%	19.2%	.710	.673	-0.37	-0.95
Orientation	6	0-6	5.92 (0.4)	0.0%	93.0%	.640	.271	-5.02	34.26
12-item version of MoCA (Total Score)	12	0-14	9.99 (2.76)	0.00%	8.7%	.703	0.712	-0.63	0.09
Final Subscales (FA Model)									
Memory Subscale	5	0-5	2.90 (1.60)	11.0%	19.2%	.673	.673	-0.37	-0.95
Multiple Subscale	7	0-9	7.22 (1.69)	0.0%	25.4%	.551	.585	-1.10	0.90

Note. Scale reliability is reported using Cronbach's alpha (α) and McDonald's omega (ω). Alpha is provided to facilitate comparability with prior MoCA studies, whereas omega (computed from polychoric correlations) is reported as a less assumption-dependent estimate for ordinal items. Total score values for the abbreviated version and for each factor are based on the sum of their component items. NE = not estimable (e.g., omega cannot be computed or is unstable for very short domains, such as two-item components); FA = factor analysis.

(Qu et al., 2025) and the prefrontal cortex network and its connectivity (Menon & D'Esposito, 2021). First, the Memory factor comprises the five delayed free recall items on the verbal episodic memory task. This set of items explores the ability to retrieve previously learned and consolidated verbal information as part of the memory process. Studies on dynamic cellular and molecular mechanisms involved in memory have identified specific neuronal engrams for the encoding, consolidation, and retrieval of information, primarily involving the hippocampus and the medial and ventromedial prefrontal cortex, among others (Tallman et al., 2024; Teng et al., 2025). While being a very specific factor, it is also a prominent one; it has been observed that worsening performance on free recall tasks can be considered a predictor of the preclinical and asymptomatic phase of Alzheimer's disease, and is even associated with plasma biomarkers (Aschenbrenner et al., 2024; Grober et al., 2022, 2023).

Secondly, the Multiple factor includes seven items exploring cognitive abilities that depend on multiple neural networks with a markedly integrative character. These include visuoconstructive and visuospatial skills, as well as the executive components of cognitive flexibility and planning (tested with the category switch, cube copying and clock drawing items), the ability to identify and name visual stimuli (lion and rhinoceros items), and the capacity for conceptual reasoning, semantic categorization, and cognitive flexibility (train-bicycle similarity item). Sustained attention, working memory, calculation, and executive control (serial subtraction items) are skills whose performance has been linked in prior neurocognitive models to distributed cortico-subcortical systems and frontoparietal control resources, rather than to a single localized network (Dragomir & Omurtag, 2021; Hobeika et al., 2016; Imai et al., 2022). All of these networks support the functioning involved in various cognitive skills that require the integration of cortical and subcortical information and share a common frontal executive component. Lesions in any area or connection involved in these networks may result in poorer performance on this second factor.

Regarding validity evidence on the basis of relationships with other variables, the associations with age and educational level were moderate and in the expected direction, supporting construct validity (Aiello et al., 2022; Pereiro et al., 2017; Sachs et al., 2022). Additionally, the associations with cardiometabolic indicators—hypertension and BMI—and with the CAIDE index suggest that MoCA scores and their factors can capture gradients of vascular and lifestyle risk with prognostic relevance (Lentoor & Myburgh, 2022). This pattern is in line with previous evidence documenting how MoCA performance worsens along the cardiovascular disease continuum (Gagnon et al., 2022) and with reviews linking cardiovascular risk indices to cognitive impairment and dementia (Jia et al., 2023). Furthermore, associations between risk scores (e.g., CAIDE/ANU-ADRI), tau pathology, and cognition have been described in community cohorts (Guo et al., 2024; Yin et al., 2024). Taken together, these findings offer validity evidence based on relationships with other score variables versus clinical markers and composite indices, although caution is required when interpreting the above, given the lack of widespread validation for this index in Spain (Geethadevi et al., 2023; Kivipelto et al., 2006; Nicotra et al., 2024). Accordingly, these associations should be interpreted as supportive correlational evidence in a community screening context, rather than as diagnostic or causal evidence.

From a psychometric perspective, the findings are consistent with studies that question domain-based dimensionality and support more parsimonious models for their stability and interpretability (Coen et al., 2016; Duro et al., 2010; Roalf et al., 2016). Consistent with this literature, none of the prespecified theoretical CFA models achieved acceptable fit. This likely reflects structural features of the MoCA in community samples: brief ordinal items with heterogeneous content and pronounced ceiling effects can attenuate the inter-item covariance needed to support complex, domain-based or hierarchical specifications. Consequently, empirically derived, parsimonious structures may show greater stability than theoretically imposed ones, in line with the cross-cultural heterogeneity reported in recent structural reviews (Sergi et al., 2025). Regarding reliability, the moderate internal consistency observed—particularly for the Multiple factor—is expected given the brevity of the subscales, the heterogeneity of the cognitive processes involved, and the marked skewness typical of non-clinical samples. In this context, classical internal consistency indices may underestimate measurement quality; therefore, interpretation benefits from a dimensional approach supported by item response theory and conditional measurement precision. Our findings align with several psychometric studies in which a relatively distinct memory factor emerges alongside factors capturing other cognitive functions of varying complexity (Cancino et al., 2020; Coen et al., 2016; Duro et al., 2010; Freitas et al., 2012, 2015). In Portugal, two well-fitting factors have been described: a memory factor and another that integrates visuospatial, attentional, and executive components (Duro et al., 2010; Freitas et al., 2012, 2015). This pattern is similar to the findings of our study, although the exact composition of the two resulting factors is not identical. Importantly, our structure was derived at the item level, whereas Duro et al. (2010) analyzed aggregated subtests; thus, our Memory factor is strictly operationalized by delayed recall, and the Multiple factor aggregates heterogeneous non-mnemonic tasks, so these factors are not isomorphic to the Verbal Memory and Executive Attention domains previously described. Similarly, comparisons with Luo et al. (2019) require caution, as their bifactor modeling was used to evaluate essential unidimensionality rather than to propose a comparable two-factor content structure. Furthermore, IRT evidence shows inconsistent information per item and ceiling effects, which encourages interpretations by profile and questionnaire abridgement based on measurement properties for screening purposes (Aiello et al., 2022; Coen et al., 2016; Roalf et al., 2016). Accordingly, we emphasize factor-level interpretation and conditional precision, together with local normative data, to support use in community screening contexts (Pereiro et al., 2017; Vallés-Salgado et al., 2024).

The results also have implications for cognitive impairment screening in community settings. The Memory factor is particularly useful in measuring delayed free recall, an episodic memory index with recognized diagnostic value (Islam et al., 2023; Nasreddine et al., 2005; Tsoi et al., 2017). Overall, the relationships between the Multiple factor and cardiometabolic risk are consistent with the hypothesis of dopaminergic decline and prefrontal compensation, changes which are characteristic of aging (Bäckman et al., 2006; Cabeza, 2002). This pattern is consistent with known modifiable targets (e.g., blood pressure and metabolic control) and suggests that monitoring by factors can provide additional information in community follow-up. At the same time, the high concordance

observed between the 12-item form and the full MoCA total score supports continuity with standard screening practice based on total scores, facilitating practical interpretation without implying structural equivalence.

Information curves indicate that the Memory factor offers greater measurement precision in the clinically relevant range for early detection, while the Multiple factor concentrates information at low levels and displays a ceiling effect at mid-to-high performance levels; a pattern consistent with the IRT literature on delayed recall, calculation, attention, and executive functions, compared to tasks with a marked ceiling effect such as orientation or naming (Luo et al., 2019; Roalf et al., 2016; Sachs et al., 2022). More specifically, peak information for the Multiple factor at very low trait levels (θ far below the mean) reflects targeting toward poorer performance (i.e., greater discrimination among lower-performing individuals), rather than a floor effect (accumulation of minimum observed scores); in a high-functioning community sample, this targeting yields limited resolution at average-to-high ability levels and is expressed as reduced differentiation near the upper end of observed performance (a ceiling-type limitation). In community settings where prevention is a priority, a factor-based interpretation can help guide referral decisions, optimize resources, and avoid unnecessary testing (Coen et al., 2016; Islam et al., 2023; Pereiro et al., 2017). Clinically, this pattern supports using the Multiple factor primarily for screening and referral when poorer performance is suspected, whereas monitoring subtle change within the normal range should be interpreted with caution and, when needed, complemented with more demanding measures and the Memory factor (Luo et al., 2019; Roalf et al., 2016; Sachs et al., 2022). In practice, this factor-level information may add value over the total score when interpreting borderline performances, monitoring change, or deciding referral in primary care and community settings. Furthermore, in individuals with high cardiovascular risk (hypertension, dyslipidemia, hyperglycaemia, or obesity), visuo-attentional markers may be sensitive to change, allowing assessment of intervention effectiveness and their impact on cognitive performance (Ngandu et al., 2015; Williamson et al., 2019). Because item selection and measurement precision depend on the intended screening purpose and the trait range where maximal precision is needed, future research should develop and cross-validate purpose-specific short forms optimized for different regions of θ using IRT information-targeting criteria and, when available, external clinical anchors (Badham et al., 2025; Mokkink et al., 2024; Roalf et al., 2016).

This study has limitations that should be considered. First, although the sample is community-based, it was assembled from primary care studies conducted in Castilla y León; therefore, generalization to other Spanish regions and sociocultural contexts should be made with caution and confirmed through external replication. The sample's sociodemographic profile was broadly comparable to official population statistics for Castilla y León, with a similar age distribution and only a modest overrepresentation of women (approximately +7 percentage points); the higher educational attainment observed is consistent with the comparatively higher educational profile of this autonomous community (INE, 2025). The cross-sectional design precludes the inference of causality, and the 12-item solution, while improving parsimony, may affect content validity; these aspects should be assessed depending on the intended use (Mokkink et al., 2024; Roalf et al., 2016). Because the 12-item form was derived by prioritizing structural replicability and measurement precision under ordinal modeling, it does not preserve the full breadth of MoCA content and should be interpreted as a dimensional screening index rather than as a substitute for domain-level clinical profiling; when domain-specific information is required, use of the full MoCA remains preferable. Furthermore, measurement invariance was not formally evaluated; therefore, comparisons between subgroups are beyond the scope of this study and should be confirmed in future research. In addition, the present study focused on a cognitive impairment-free community sample; although clinical groups (e.g., MCI or dementia) were not included, validation in these populations is an important direction for future research. Excluding participants with diabetes may also limit generalizability to populations with metabolic comorbidities, and future studies should examine whether the measurement structure identified here remains stable when these individuals are included. Finally, validity evidence against external clinical criteria (e.g., standardized neuropsychological batteries, clinical diagnoses, or biomarker-informed outcomes) was not available; therefore, any short-form cut-off should be regarded as a linkage to the conventional MoCA threshold rather than an independently validated clinical decision rule. Likewise, because no neurobiological measures (e.g., neuroimaging or biomarkers) were collected, neurocognitive interpretations should be understood as theoretical contextualization rather than empirical evidence of neural substrates or causal mechanisms. However, this does not affect the internal validity of the structure and the estimated measurement properties. Strengths include the large sample size and age range, a psychometric approach aligned with current standards, and high agreement between the total score of the original format and the abbreviated version, all of which support the relevance of this study (American Educational Research Association et al., 2014; Kline, 2023; Roalf et al., 2016).

In conclusion, the results support a MoCA structure composed of 12 items grouped into two correlated factors in a large cognitive impairment-free Spanish community sample. This structure is parsimonious, interpretable, and consistent with hierarchical cognitive models. The Memory factor offers greater accuracy in the range relevant for early screening, while the Multiple factor provides more information at low levels and shows a ceiling effect at medium-to-high performance levels; a pattern consistent with the IRT-based literature. Therefore, supplementing the total score with factor profiles and demographic adjustments is a recommended strategy for detection and referral in community settings. These findings support the 12-item form as a brief screening option anchored to the standard MoCA metric, whereas clinical profiling requiring broader content coverage remains better served by the full MoCA (Mokkink et al., 2024; Roalf et al., 2016). Future priorities include conducting longitudinal studies, using adjusted normative data, studying measurement invariance, benchmarking the 12-item form and factor scores against external clinical criteria in independent samples, and developing clinical decision support tools, such as IRT-based calculators, to facilitate translation into clinical practice.

Author Contributions

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Declaration of Interests

The authors declare that there are no conflicts of interest.

Data Availability Statement

The dataset, analysis scripts, and supplementary materials generated for this study have been deposited in the Zenodo repository.

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