The psychometric properties of the Montreal Cognitive Assessment (MoCA): A comprehensive investigation

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Abstract

Background

The Montreal Cognitive Assessment (MoCA) is a common tool for the assessment of global cognition in older adults. Despite its popularity among clinicians and researchers, the test's psychometric properties are still uncertain.

Objective

To examine fundamental psychometrics properties of the MoCA that have not been established so far (i.e., factorial structure, general factor saturation, and measurement invariance).

Design

Cohort study.

Setting

Population-based invitation-type survey in city and rural areas in Hyogo prefectures and Tokyo Metropolitan, Japan.

Subjects

Individuals ($N = 2,408$) aged 69 to 91 clustered in three cohorts (69-71-year-olds, 79-81-year-olds, and 89-91-year-olds).

Methods

Exploratory Factor Analysis and Confirmatory Factor Analysis.

Results

The MoCA shows an overall stable hierarchical factorial structure and a satisfactory general factor saturation. Also, measurement invariance occurs across participants with different age, educational level, economic status, and gender.

Conclusion

This comprehensive investigation upholds the idea that the MoCA is a psychometrically valid tool for the assessment of global cognition in older adults.

Key points

- The Montreal Cognitive Assessment (MoCA) is a common test for evaluating global cognition in older adults.

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- The MoCA has never undergone a thorough analysis to test its psychometric properties.
- The study evaluates the test's dimensionality, factorial structure, general factor saturation, and invariance.
- The results show that the test's items perform well in all the analyses.
- The MoCA is thus a reliable tool for assessing global cognition in older adults.

Keywords: cognition; factor analysis; measurement invariance; MoCA; older adults.

Introduction

The Montreal Cognitive Assessment (hereafter MoCA) [1] is one of the most common tests for measuring global cognition and detect potential global cognitive impairment in older adults. Administering the MoCA is quick (approximately ten minutes), and the test can be used with both older adults and old-older adults (e.g., > 80-year-old). The test is thus a useful and convenient instrument for the study of cognitive function (and dysfunction). For these reasons, the MoCA is currently employed by researchers and clinicians all over the world, as testified by the numerous citations of Nasreddine and colleagues' article (more than 10,000 citations in Google Scholar, as of December 2019).

The MoCA has been designed to measure a construct of interest, that is, the subject's global cognition. Consequently, the MoCA total score is supposed to be a measure of this construct. Nonetheless, some fundamental psychometric properties of the MoCA's items are still unclear. Specifically, their factorial structure, reliability, and measurement invariance have not been satisfactorily investigated so far. Without establishing these properties, any inferences based on the MoCA's scores remain doubtful.

When analyzing the factorial structure of a test's items, three cases are possible. First, only one latent general factor is present (i.e., unidimensionality). In this case, the test does measure just one construct of interest with a certain degree of reliability. Second, more than one latent factor is estimated (i.e., multidimensionality), but no general factor is present. In this case, the total test score is not particularly meaningful because it does not refer to any general construct. Finally, the following case is possible: the factorial structure of the test is multidimensional but, at the same time, all the test items correlate with each other, which suggests the presence of a general factor. In this case, the total test score is indeed a measure of the putative general factor. However, the reliability of the test's total score cannot be estimated with an index such as Cronbach's α . In fact, like any other total factor saturation index, α is not trustworthy when the assumption of unidimensionality is not met [2]. Rather, an index of general factor saturation – that is, the proportion of the total

score variance of a test accounted for by a single common factor [3] – is necessary to evaluate the reliability of the test correctly (e.g., McDonald's ω and Revelle's β) [4].

Whether the MoCA score reflects only one general factor (unidimensionality) or more factors (with or without a general factor) is still a matter of debate. In some studies, unidimensionality has simply been postulated [1,5]. Other studies have provided some evidence that the MoCA's items are substantially unidimensional [6,7]. However, these studies implement Generalized Partial Credit Modelling [8] that requires summing clusters of the MoCA's items into seven sub-scores (i.e., the clusters indicated by Nasreddine and colleagues). Although viable, this approach postulates, rather than tests, a specific structure in the data. Such a priori assumptions about the MoCA's data structure have also been employed with factor analysis [9,10]. In these cases, the MoCA's items have been found to be multidimensional with no general factor, but the number of factors is unclear. Finally, other researchers have adopted a more exploratory approach and highlighted the tendency of the MoCA's items to converge towards a multidimensional structure with a general factor [11]. However, no index of general factor saturation is provided.

Finally, no thorough analysis of measurement invariance has been performed on the MoCA so far. This gap in the literature is particularly concerning. Measurement invariance is a crucial property for any test because it concerns whether the test's total scores have the same meaning under a set of different conditions (e.g., between genders and across participants of different age). Without establishing measurement invariance, it is impossible to make any meaningful comparison across groups. Therefore, this state of affairs makes the interpretation of MoCA scores problematic.

There are several hierarchically organized levels of measurement invariance [12]. The least restrictive one is *configural invariance*, which denotes whether a test's items show the same factorial structure across conditions. *Weak invariance* (also referred to as *metric invariance*) assumes configural invariance and requires the same factor loadings across groups and thus establishes that the constructs measured by the test's total scores are manifested in the same way across groups. Simply put, this condition tells us that responses

on the items refer to the latent constructs with the same metric across groups. *Strong invariance* (also referred to as *scalar invariance*) assumes weak invariance and requires the same intercepts across groups. Finally, the most restrictive level is *strict invariance*, which requires both strong invariance and equal items' variances across groups. Strict invariance, therefore, provides information about how precisely the construct of interest is measured.

This study implements a systematic analytical strategy to address the above issues. First, we establish whether the items of the MoCA subtend either a unidimensional or multidimensional (with or without a general factor) structure. Second, we use exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to determine the exact factorial structure of the MoCA. Third, we provide several reliability indexes for both general factor saturation and total factor saturation. Finally, we test for measurement invariance in four fundamental demographic variables – age, educational level, economic status, and gender – that may constitute confounding elements in the assessment of global cognition.

Methods

Participants

The study included a total of 2,408 Japanese older adults. The participants were organized in three cohorts accordingly to their age range (69-71, 79-81, and 89-91). The data were retrieved from the SONIC survey and referred to baseline assessment. All the details regarding the SONIC survey can be retrieved from [13].

Variables

MoCA. We used the data of the Japanese translation of the MoCA. For more details, see [14]. As in Freitas and colleagues' study [11], the 32 dichotomous (0/1) items of the test were used in the analyses.

Demographics variables. We examined gender (male, female), age cohort (see above), education, and self-reported economic status of the participants. Education included three levels indicating the highest educational degree achieved by the participant

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(primary/middle school, high school, and university/college education). The economic status of the participants included three levels as well (no financial leeway, some financial leeway, good financial leeway).

Analytical approach

We employed a systematic strategy. First, we calculated the percentage of correct responses in each item of the MoCA. Second, we ran several unidimensionality tests. Third, we ran an exploratory factor analysis (EFA) to investigate the factorial structure of the MoCA in a randomly selected subsample [2]. Fourth, the results of the EFA were tested with confirmatory factor analysis (CFA) that included all the observations not used in the EFA model. Finally, we tested measurement invariance of the MoCA score between genders, age cohorts, educational level, and self-reported economic status.

Results

Descriptive statistics

The descriptive statistics are summarized in Table 1.

Table 1

MoCA total scores sorted by age cohorts, educational levels, economic status, and gender

<u>Age/Cohort</u>	<i>70-year-old</i>	<i>80-year-old</i>	<i>90-year-old</i>	<i>Total</i>
<i>N</i>	970	943	495	2,408
<i>Mean (SD)</i>	24.03 (3.66)	22.28 (4.29)	20.24 (5.15)	22.56 (4.48)
<u>Education</u>	<i>Primary/Middle</i>	<i>High School</i>	<i>College/University</i>	<i>Total</i>
<i>N</i>	824	889	695	2,408
<i>Mean (SD)</i>	20.36 (4.61)	23.53 (3.94)	23.94 (3.95)	22.56 (4.48)
<u>Gender</u>	<i>Males</i>	<i>Females</i>	<i>-</i>	<i>Total</i>
<i>N</i>	1,138	1,270	-	2,408
<i>Mean (SD)</i>	22.64 (4.26)	22.50 (4.66)	-	22.56 (4.48)
<u>Economic Status</u>	<i>No Leeway</i>	<i>Some Leeway</i>	<i>Good Leeway</i>	<i>Total</i>
<i>N</i>	488	1328	592	2,408
<i>Mean (SD)</i>	21.86 (4.48)	22.53 (4.52)	23.22 (4.28)	22.56 (4.48)

Data preparation

We examined the mean correct response rate on each of the 32 items of the MoCA. To avoid estimation problems related to ceiling effect (e.g., inflated item complexity in EFA), we excluded those items whose mean correct response was above 95% ($n = 5$). All the following analyses were thus performed with the remaining 27 dichotomous items of the MoCA. In addition, in order to control for any differences introduced by this technical choice, we replicated the analyses including all the 32 items. Only negligible differences were found (see the Supplemental materials).

Dimensionality tests

We first ran a unidimensionality check on a Rasch model [15,16]. The analyses were performed with the *ltm* R package [17,18]. This analysis showed evidence of multidimensionality ($p < .010$). We then ran a parallel analysis [19] to establish the number of first-order factors with the *psych* R package [20]. The tetrachoric correlation matrix and the weighted least squares (WLS) estimator were used. The parallel analysis estimated eight factors. The inspection of eigenvalues suggested the presence of a general factor (first eigenvalue = 6.40, second eigenvalue = 1.67).

Exploratory Factor Analysis

The previous analyses established that our data showed a multi-factorial structure. First, following standard guidelines [21], we randomly selected half of the participants ($N = 1,204$; calibration sample), while the other half of the sample was used in the CFA analysis (see below). We then ran a hierarchical EFA with seven first-order factors and assuming a general factor, as indicated by the parallel analysis. We performed the analyses with the *psych* R package. All the items loaded onto the general factor (g). The seven sub-factors approximatively corresponded to the seven subsets indicated by Nasreddine and colleagues. Overall, the items thus exhibited a stable multi-factorial structure. Table 2 summarizes the results of the EFA.

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Table 2

Results of the EFA model

<i>MoCA Item</i>	<i>g</i>	<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	<i>F5</i>	<i>F6</i>	<i>F7</i>	<i>h²</i>	<i>u²</i>
Q1.TRAIL MAKING	0.54	0.09	-0.03	0.10	0.20	0.16	0.31	0.03	0.47	0.53
Q2.CUBE	0.41	0.05	0.12	-0.10	0.24	0.00	0.35	0.02	0.40	0.60
Q3.CLOCK HAND	0.44	-0.08	0.03	0.08	-0.03	0.03	0.45	0.10	0.41	0.59
Q3.CLOCK SHAPE	0.49	0.04	-0.01	0.07	-0.01	0.03	0.49	0.04	0.48	0.52
Q4.NAMING CAMEL	0.47	-0.02	-0.01	0.19	-0.03	0.50	0.02	0.04	0.50	0.50
Q4.NAMING LION	0.38	-0.02	0.00	-0.05	0.06	0.66	-0.03	0.04	0.60	0.40
Q4.NAMING RHINO	0.52	0.15	0.13	-0.02	-0.11	0.48	0.17	-0.02	0.58	0.42
Q6.DIGIT SPAN BACKWARD	0.34	0.08	0.14	-0.03	0.41	0.01	0.05	0.02	0.32	0.68
Q6.DIGIT SPAN FORWARD	0.36	0.01	0.04	-0.01	0.39	0.11	0.10	0.04	0.32	0.68
Q7.ATTENTION	0.43	0.13	0.05	0.17	0.24	0.04	0.07	0.03	0.30	0.70
Q8.SUBTRACTION 86	0.41	-0.02	0.40	0.12	0.10	-0.05	0.12	-0.09	0.39	0.61
Q8.SUBTRACTION 79	0.42	0.01	0.62	-0.04	-0.02	0.05	0.05	-0.04	0.57	0.43
Q8.SUBTRACTION 72	0.46	-0.01	0.74	0.01	0.01	-0.02	-0.06	0.05	0.76	0.24
Q8.SUBTRACTION 65	0.47	0.02	0.54	0.06	0.00	0.05	0.03	0.02	0.51	0.49
Q9.WORD REPETITION 1	0.31	0.01	0.04	0.04	0.41	-0.10	0.02	0.19	0.33	0.67
Q9.WORD REPETITION 2	0.39	-0.08	0.12	0.15	0.30	0.15	-0.07	0.09	0.32	0.68
Q10.VERBAL FLUENCY	0.39	0.11	0.04	0.00	0.20	0.25	0.11	-0.02	0.28	0.72
Q11.ABSTRACTION 1	0.37	0.03	0.01	-0.03	0.03	-0.01	0.03	0.64	0.54	0.46
Q11.ABSTRACTION 2	0.40	0.07	-0.01	0.10	-0.03	0.05	0.05	0.44	0.37	0.63
Q12.RECALL 1	0.32	0.55	0.05	0.08	-0.16	-0.04	-0.01	0.08	0.47	0.53
Q12.RECALL 2	0.39	0.61	0.03	-0.04	0.00	0.10	-0.05	0.09	0.53	0.47
Q12.RECALL 3	0.45	0.58	-0.04	0.12	0.18	0.05	-0.04	-0.02	0.61	0.39
Q12.RECALL 4	0.41	0.68	0.04	-0.03	0.01	-0.07	0.12	-0.03	0.64	0.36
Q12.RECALL 5	0.40	0.67	-0.03	0.05	0.00	0.03	-0.02	0.02	0.63	0.37
Q13.ORIENTATION YEAR	0.63	-0.07	0.07	0.72	0.00	0.02	0.02	0.06	0.90	0.10
Q13.ORIENTATION DAY	0.60	0.20	0.00	0.65	0.01	-0.03	0.02	-0.03	0.88	0.12
Q13.ORIENTATION PLACE	0.43	-0.04	-0.06	0.38	0.08	0.16	0.08	0.00	0.35	0.65

Note. *Item* = the item of the MoCA; *g* = general factor; *F1* = factor 1; *F2* = factor 2; *F3* = factor 3; *F4* = factor 4; *F5* = factor 5; *F6* = factor 6; *F7* = factor 7; *h²* = communality of the item; *u²* = uniqueness of the item.

Confirmatory Factor Analysis

We built a hierarchical CFA model following the results of the EFA. We used the other half of the sample. This model included seven first-order factors loading onto one second-order factor. Since the indicators were dichotomous, we used the WLSMV estimator. We performed these analyses with the *lavaan* and *semTools* R packages [22,23].

We calculated the statistical power for not-close fit hypothesis testing [24]. Assuming the null RMSEA = .050, alternative RMSEA = .010, the statistical power was more than adequate (> 99%) for global fit testing and rejection of false models (5% significance threshold). The CFA model exhibited good fit, $\chi^2_{(317)} = 453.776, p < .001$, RMSEA = .019, and SRMR = .063, CFI = .970, and NCI = .972 [25]. The model estimated by the EFA analysis was thus confirmed by the CFA model in an independent sample.

Reliability indexes

We calculated McDonald's omega (ω) coefficients and Revelle's beta (β) coefficient to measure the general factor saturation of the MoCA. The percentage of the reliable (i.e., not due to random error) variance – the ratio between omega hierarchical (ω_h) and omega total (ω_t) multiplied by 100 [3] – in the MoCA total scores accounted for by the general factor g was satisfactory (74%; $\omega_h = .68$ and $\omega_t = .92$). Revelle's beta, which represents the minimum split-half reliability, was adequate too ($\beta = .78$). Total factor saturation indexes were similar to ω_t (Cronbach's $\alpha = .89$ and Guttman's $\lambda_6 = .91$).

Measurement invariance

Finally, we tested whether the MoCA's items exhibited configural, weak, and strict invariance across the age groups, education level, gender, and economic status of the participants (strong invariance cannot be tested with dichotomous indicators). We performed these analyses on the whole sample ($N = 2,408$) with the *semTools* R package.

The analyses were run according to the guidelines provided by Chen and colleagues, Rudnev and colleagues, and Wu and Estabrook [26–28]. First, configural invariance was tested by imposing the model's threshold to be equal across groups. Second, we tested two types of weak invariance by imposing equality constraints to (a) the factor

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loading between first-order factors and the observed variables (i.e., the items of the test; Weak – 1st) and then (b) all the factor loadings (Weak – Full). Finally, strict invariance was first tested by applying equality constraints to the first-order factors' variances (the variances of the indicators were fixed to 1 in the configural model) [28].

Measurement invariance was tested by inspecting the difference (Δ) in fit indexes in increasingly constrained models (e.g., configural vs. weak). The thresholds for model rejection were: $\Delta RMSEA > .015$, $\Delta SRMR > .030$, $\Delta CFI < -.010$, and $\Delta NCI < -.020$ [29,30]. Measurement invariance was confirmed for all the four demographic variables. None of the fit indexes reached its threshold for model rejection (maximum $\Delta RMSEA = +.001$; $\Delta SRMR = +.005$; $\Delta CFI = -.003$; $\Delta NCI = -.006$). Moreover, the chi-squared different test, whose Type I error rate is notoriously high, barely reached statistical significance in only one case ($p = .044$). Table 3 summarizes the results of this analysis.

Table 3

Summary of the Measurement Invariance Analysis

	χ^2	<i>df</i>	<i>p-value</i>	<i>RMSEA</i>	<i>SRMR</i>	<i>CFI</i>	<i>NCI</i>
Age							
<i>Configural</i>	1171.289	930	-	.018	.079	.972	0.951
<i>Weak – 1st</i>	1213.124	970	.207	.018	.082	.972	0.951
<i>Weak – Full</i>	1252.537	982	.044	.019	.087	.969	0.945
<i>Strict</i>	1277.572	996	.085	.019	.087	.967	0.943
Education							
<i>Configural</i>	1172.227	930	-	.018	.077	.970	0.951
<i>Weak – 1st</i>	1214.340	970	.229	.018	.081	.970	0.951
<i>Weak – Full</i>	1208.505	982	.545	.017	.082	.972	0.954
<i>Strict</i>	1234.239	996	.075	.017	.083	.970	0.952
Gender							
<i>Configural</i>	793.382	620	-	.015	.058	.983	0.965
<i>Weak – 1st</i>	782.599	640	.923	.014	.059	.986	0.971
<i>Weak – Full</i>	799.263	646	.093	.014	.061	.985	0.969
<i>Strict</i>	800.430	653	.754	.014	.061	.985	0.970

Wealth							
<i>Configural</i>	1135.111	930	-	.017	.071	.978	0.958
<i>Weak – 1st</i>	1153.828	970	.505	.015	.073	.981	0.963
<i>Weak – Full</i>	1150.744	982	.515	.015	.074	.982	0.966
<i>Strict</i>	1157.154	996	.636	.014	.075	.983	0.967

Note. χ^2 = Scaled Chi Squared; *Df* = Degrees of freedom of the model; *p-value* = significance of the scaled Chi-Squared difference test; *RMSEA* = Root Mean Square Error of Approximation (scaled); *SRMR* = Standardized Root Mean Square Residual; *CFI* = Comparative Fit Index (scaled); *NCI* = Non-Centrality Index (scaled).

Discussion

The aim of this paper was to evaluate the psychometric properties of the MoCA's items in a large sample of Japanese older adults. Specifically, we have investigated (a) the dimensionality of the MoCA's items; (b) their factorial structure; (c) their total factor saturation and general factor saturation; and (d) whether measurement invariance occurs across a set of fundamental demographic variables such as age, education, economic status, and gender. The analytical strategy implemented includes a set of exploratory methods (parallel analysis and EFA) and confirmatory methods (CFA and measurement invariance analysis). This choice has allowed us to cross-validate the factorial structure of the test's items in two independent samples without applying any a priori data structure (e.g., summing the items according to Nasreddine et al.'s categorization [1]).

The results show that the MoCA is, overall, a valid tool for assessing global cognition in older adults. First, the presence of a general factor – along with seven sub-factors – indicates that the test's total score is indeed a measure of global cognition. This factorial structure is verified in both the EFA and CFA models. Second, the reliability of the MoCA's items is adequate in terms of both total factor saturation ($\alpha = .89$ and $\lambda_6 = .91$) and, most notably, general factor saturation ($\omega_h/\omega_t = .74$ and $\beta = .78$). Third, measurement invariance occurs is confirmed from the least restrictive model (configural invariance) to the most restrictive model (strict invariance) in all the demographic variables examined. This finding is of particular interest because no previous investigation has ever included a

comprehensive measurement invariance analysis of the MoCA. (It is worth noting that Luo et al. [7] have tested measurement invariance analysis between subjects with and without formal education in a Chinese sample and found that most of the items are invariant.)

Furthermore, the present study may offer some insights regarding the inconsistent outcomes provided by the literature so far. As seen, measurement invariance analysis and general factor saturation have substantially remained untested. By contrast, the research on the MoCA's dimensionality and factorial structure has been somewhat more abundant but has produced mixed results. Our investigation corroborates the assumption of a general factor made by several previous studies [1,5–7]. The only difference is that these studies report that the general factor is also the only latent dimension in the data (unidimensionality). The difference with our results, which suggest multidimensionality in the MoCA's items, simply stems from a methodological choice. In fact, we have not imposed any a priori constraint to the data (e.g., summing sets of items) that would conceal the true hierarchical factorial structure of the test's items.

Conclusions

The present study reports a comprehensive psychometric analysis of the MoCA. The test shows a stable hierarchical factorial structure, satisfactory general factor saturation, and measurement invariance in key demographic variables. The MoCA is thus a reliable tool for assessing global cognition in older adults.

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