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Cognitive reorganization in patients with Parkinson's Disease and Mild Cognitive Impairment: a neuropsychological network approach

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Parkinson's Disease (PD) exhibits heterogeneous cognitive deficits that may represent different cognitive phenotypes. While previous studies have described them in a "macro" manner, only one study has applied Network Analysis (NA) in PD. NA represents a model to explore relationships between cognitive abilities, aiding in understanding cognitive phenotypes. This study aims to verify whether the cognitive system undergoes reorganization in PD with Mild Cognitive Impairment (PD-MCI) patients. To explore this, a Level II cognitive assessment was administered to 275 PD patients, who were classified into two diagnostic categories: PD-Cognitive Unimpaired (CU) ($n = 171$) and PD-MCI ($n = 104$). NA was applied to construct Gaussian Graphical Models for each diagnostic group, where *nodes* represent cognitive tests and demographic factors, and *edges* represent their interconnections. The NA revealed substantial differences between the cognitive networks of PD-CU and PD-MCI patients. Specifically, the network of PD-MCI patients appears less sparse, with some weakened relationships between nodes. Overall, the results support the presence of a cognitive reorganization in PD-MCI patients, potentially indicating a functional compensation mechanism. In conclusion, this study enhances the understanding of the cognitive mechanisms underlying cognitive decline in patients with PD.

Keywords Parkinson's Disease, Network Analysis, Cognitive reorganization, Mild cognitive impairment, Functional compensation

In clinical neuropsychology, the neuropsychologist assesses a patient's cognitive performance to identify cognitive phenotypes to support medical diagnosis. However, cognitive tests require various abilities beyond the one for which the test was originally designed[1]. For instance, while the Action Naming test is primarily considered to assess lexical access, it also requires visual-perceptual abilities. Moreover, a naming deficit may result from either a failure in lexical retrieval or an underlying semantic memory disorder. Therefore, the interpretation of cognitive tests is crucial for understanding the cognitive phenotypes of a particular disease.

The exploration of cognitive phenotypes is a topic of interest in many neurological conditions, such as Parkinson's Disease (PD). PD is a neurodegenerative disorder that encompasses both motor and non-motor symptoms, with cognitive deficits being particularly debilitating[2]. These impairments significantly affect patients' functional independence and quality of life, as well as that of caregivers[2]. Cognitive deficits span over multiple cognitive domains, although the typical PD patient exhibits a dysexecutive syndrome, cognitive impairments can also affect memory, language, visuospatial abilities, and social cognition[3–5]. Similarly to Alzheimer's disease (AD), cognitive deficits in PD may progress from mild cognitive impairment (PD-MCI) to dementia (PD-D). PD-MCI is a condition characterized by different clinical features[6]and its diagnosis relies on the criteria established by the Movement Disorders Society (MDS)[7].

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Due to the different nature of cognitive disorders, numerous studies have attempted to define cognitive phenotypes that can effectively characterize PD patients[8–12]. For example, Barvas et al[8]. employed Latent Profile Analysis (LPA) in a study of 65 PD patients, identifying three distinct cognitive clusters: Cluster A, comprising patients with intact cognitive function or mild executive and memory deficits; Cluster B, characterized by a moderate cognitive decline; and Cluster C, which exhibited severe cognitive impairments, particularly in executive functions and visuospatial abilities.

While previous studies have focused on identifying phenotypes by clustering symptoms, Network Analysis (NA) enables the exploration of the connections between these symptoms. Examining these connections can offer valuable insights into the functioning of the cognitive system in complex disorders such as PD.

NA serves as an abstract model for studying and representing potential relationships between nodes, such as cognitive tests. In NA, nodes are interconnected through edges, which shows the degree of association between the nodes. Only in the last ten years, NA has gained attention in the field of psychology and mental health, finding applications in areas such as clinical psychology[13–15], psychiatry[16,17], personality[18], and social psychology[19].

In neuropsychology, only a limited number of studies have employed NA, despite cognitive tests being well suited for exploring interrelationships, according to the between-domain model[20]. Specifically, NA has been applied to study neurodegenerative disorders[20–23], epilepsy[24], and stroke[25]. Concerning PD, to the best of our knowledge, only a single study employed NA. Specifically, Ferguson and Foley (2023)[21] examined data from 198 healthy controls (HC) and 293 PD de novo from the Parkinson's Progression Markers Initiative (PPMI) database. Both groups completed a brief neuropsychological assessment, including tests for speed processing (Symbol Digit Modalities Test), verbal episodic memory (Hopkins Verbal Learning Test-Revised) working memory (Letter-Number Sequencing), and visuospatial skills (Line Orientation Judgments). The results revealed that in PD patients, working memory and information processing speed were strongly associated with other cognitive abilities, whereas the HC group exhibited a less connected and sparser network. Based on these findings, the authors concluded that working memory (WM) and information processing speed are particularly influential variables in the global cognitive functioning of PD patients. However, it is important to consider that the authors did not distinguish patients by cognitive status, instead compared patients with PD (with or without cognitive impairments) to a control group without the disease.

In contrast, we aim to investigate the relationship between cognitive abilities in cognitively unimpaired PD (PD-CU) patients and PD-MCI patients. The objective is to determine whether the cognitive system undergoes reorganization in PD-MCI patients.

Methods

Participants

The study enrolled a cohort of 275 PD patients with a Hohen & Yahr (H&Y) score of ≤ 3, who were fluent in Italian and had undergone a comprehensive level II cognitive assessment[7]. Patients diagnosed with atypical parkinsonism, an H&Y score greater than 3, or those with dementia, advanced therapy, genetic mutations, or other neurological or psychiatric disorders were excluded from the study.

Ethics approval and consent to participate

The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the University of Trento. All methods were performed in compliance with the relevant guidelines and regulations. Informed consent was obtained from all participants.

Neuropsychological assessment and patients' diagnostic classification

All patients underwent a comprehensive Level II neuropsychological assessment following the MDS criteria[7]. The test battery encompassed various cognitive domains, based on the evidence that this battery classified patients in PD-CU or PD-MCI with an accuracy of 90.6%[26]. The battery included the Montreal Cognitive Assessment (MoCA)[27]for cognitive screening, the Digit Span Backward[28]and Trail Making Test Part B minus Part A (TMT B-A)[29]to assess attention and working memory, the Rey Auditory Verbal Test–Immediate Recall (RAVLT-IR)[30], and the Rey-Osterrieth Complex Figure–Delayed Recall (ROCF-DR)[31]for episodic memory. Executive functions were assessed by means of the Stroop Test (time parameter of inhibition condition)[32]and the Rey-Osterrieth Complex Figure–Copy (ROCF-C)[31]. Language abilities investigation included Semantic Fluency[33]and Action Naming[34]. Visuospatial abilities were evaluated using the Line Orientation Judgment (LOJ)[35]test and the Ekman Test[36], which assesses emotion recognition from facial expressions and requires visuoperceptual processing. Consequently, this test evaluates both visuoperceptual skills (similar to the Unknown Face Recognition test) and social cognition. As in Longo et al. (2024)[26], we followed the MDS criteria[7], but we also considered it crucial to assess the domain of social cognition. Patients were classified as PD-CU or PD-MCI according to the Italian normative cut-off scores and following the MDS criteria[7]and subsequent modifications proposed by Longo et al[26]. Specifically, for Level II criteria, MDS recommends the administration of at least two tests for each cognitive domain, namely (i) attention and working memory, (ii) executive functions, (iii) memory, (iv) language, (v) visuospatial functions. We classified as PD-MCI all patients with at least two impaired tests, one of which could be the Ekman test. As reported, patients meeting the criteria for dementia were excluded from the study.

Analyses

Statistical analysis

Descriptive analyses were conducted to characterize the sample. Means, standard deviations, and frequencies for the clinical-demographic variables and cognitive tests were computed. JASP software (Version 17.2.1) was used.

Network analysis

NA represents an abstract model for understanding the relationship between variables, necessitating a defined set of nodes and edges. In this study, we used the Joint Graphical LASSO Model (JGL). The nodes are represented by the raw scores of neuropsychological tests, along with age, education, and biological sex. Edges were established using regularized partial correlations, allowing the calculation of the relationship between two variables while eliminating the influence of other correlated variables. The regularization process was achieved using the application of the Least Absolute Shrinkage and Selection Operator (LASSO) algorithm[37]. This model supports robust multigroup network analysis by applying a second level of regularization to minimize small differences between group weight matrices, a method that filters out random variations. This algorithm, in turn, employed the extended Bayesian Information Criterion (eBIC)[38] for criterion selection, effectively controlling overfitting and contributing to the accuracy of the model. We set the gamma value that controls the eBIC at 0.

Missing values (less than 2%) were imputed using the KNN approach as implemented in the VIM package[39].

For each network we reported the graph of the weighted and signed correlations surviving the regularization procedures. These values are also reported in Table 3 alongside the basic Pearson's correlations.

Among the various measures of centrality, the following were considered and reported after standardization:

- Strength: the sum of all the edges connected to a node;
- Betweenness: the count of short connections passing through the node of interest. This measure provides insights into whether the node functions as a mediator, facilitating relationships with other nodes. The underlying principle is that the most critical connections are the shortest ones.

There are no cut-off values to interpret the centrality indices, which must be read in context as relative measures (i.e., what matters is the relative rank in a set of variables and not the actual centrality value). Notably, they have been reported in their standardised form as typically in the literature[40].

Networks were estimated using the Fuse Graphical LASSO method[41]. This method adds a second regularization parameter as compared to the basic Gaussian Graphical Models, which used to tune the similarity of the network estimations. The Fuse Graphical LASSO method maximizes the similarities between the two networks, so that the remaining differences result particularly consistent after two rounds of regularization. Tuning parameter was set at 0, lamba 1 and 2 (i.e., the penalisation parameters) were estimated simultaneously. The graphs were estimated adopting the R package EstimateGroupNetwork (https://cran.r-project.org/web/packages/EstimateGroupNetwork/EstimateGroupNetwork.pdf).

Results

Applying the diagnostic criteria, 171 patients were classified as PD-CU and 104 as PD-MCI. The specifics regarding clinical variables can be found in Table 1, while the means and standard deviations of cognitive test performances are presented in Table 2.

Cognitive network of PD-CU patients

The network of PD-CU patients included 14 nodes and 35 edges, with a sparsity value of 0.38, reflecting a fairly dense network (Fig. 1; see Table 3 for correlation values).

Notably, age, education, and biological sex displayed connections to several nodes. The centrality indices reveal the pivotal role of biological sex in the network, suggesting its facilitating function between nodes. These findings underscore that demographic factors, particularly biological sex, significantly influence scores on various cognitive tests, highlighting several correlations among them. Specifically, age negatively correlated with test performance, indicating a decline with advancing age. In contrast, education showed predominantly positive correlations, suggesting an improvement in performance with increased education. Regarding biological sex, descriptive analyses showed superior female performance in RAVLT-IR and Ekman Test, while males performed better than females in LOJ.

MoCA showed extensive connections with the majority of nodes, demonstrating high centrality indices. The high degree of centrality indicates that MoCA is linked with most components of the network through several connections, while the high betweenness signifies that MoCA acts as a mediator in the relationships between

Clinical data	PD-MCI	PD-CU	t(df)	X^2	*p*	SE Cohen's d
N	104	171	/	/	/	/
Age, y (mean±sd)	69.18±8.22	66.45±7.92	-2.727(273)	/	0.007	0.126
Biological sex (M/F)	64/40	102/69	/	0.096	0.756	/
Education, y (mean±sd)	9.48±3.48	10.84±4.03	2.867(273)	/	0.004	0.126
LEDD, mg (mean±sd)	590.05±360.67	500.24±364.89	-1.988(273)	/	0.048	0.125
H&Y (mean±sd)	2.26±0.66	1.83±0.65	-5.221(273)	/	<0.001	0.129
Motor phen. (AR/T)	57/47	82/89	/	1.216	0.270	/
Motor lat. (R/L)	58/46	90/81	/	0.256	0.613	/
Disease duration, months (mean±sd)	79.35±51.65	58.39±58.22	-1.578(273)	/	0.116	0.125

Table 1. Clinical data of PD patients. AR/T=akinetic-rigid /tremor; H&Y=Hoehn and Yahr scale; LEDD=Levodopa Equivalent Daily Dose; MoCA=Montreal Cognitive Assessment; M/F=male/female; Motor lat.=motor lateralization at onset; Motor phen.=motor phenotype at onset; N=number; R/L=right/left.

Cognitive test	Range	Cut-off*	PD-MCI	PD-CU	t(df)	*p*	SE Cohen's d
			Mean (±sd)	Mean (±sd)			
MoCA	0-30	< 17.363	19.76±3.95	24.29±3.26	10.390(266)	<0.001	0.145
Digit Bw	0-8	< 2.65	3.61±0.74	4.28±0.86	6.540(272)	<0.001	0.132
RAVLT-IR	0-75	< 28.53	30.94±10.06	41.47±9.58	8.623(270)	<0.001	0.138
ROCF-C	0-36	< 28.88	25.06±5.97	30.55±4.24	8.758(267)	<0.001	0.140
ROCF-DR	0-36	< 9.47	9.69±4.65	15.81±6.09	8.580(266)	<0.001	0.140
Ekman[f]	0-60	< 37.46	38.34±7.39	45.82±5.35	9.193(244)	<0.001	0.148
Stroop (time)	0-∞	> 36.91	41.11±26.41	23.76±11.18	−7.409(263)	<0.001	0.137
TMT B-A	0-∞	> 186	195.34±88.57	94.13±53.50	−11.355(253)	<0.001	0.155
Act. Naming	0-50	< 36.87	42.21±5.96	47.09±3.07	8.544(249)	<0.001	0.145
Sem. Flu.	0-∞	< 23.59	30.76±9.49	42.34±10.57	9.101(270)	<0.001	0.139
LOJ	0-30	< 19	17.57±6.04	22.32±4.04	7.481(251)	<0.001	0.142

Table 2. Means and standard deviations (sd) of cognitive tests. *cut-offs are based on Italian norms.Legend: Act. Naming=Action Naming Test; Digit Bw=Digit Span Backward; LOJ=Line Orientation Judgment; MoCA=MontrealCognitive Assessment; RAVLT-IR=Rey Auditory Verbal test–Immediated Recall; ROCF-C=Rey-Osterrieth Complex Figure–Copy;ROCF-DR=Rey-Osterrieth Complex Figure–Delayed Recall; Sem. Flu.=Semantic Fluency Test; TMT B-A=Trail Making Test PartB minus part A.

various cognitive tests. Specifically, these findings suggest that MoCA is a broad and nonspecific test, consistent with what is expected from screening tests.

Moreover, the topographic and centrality analysis highlights that both RAVLT-IR and Semantic Verbal Fluency are central tests within the network. These tests exhibit extensive connections with other tests and play a facilitating role in mediating relationships with other tests.

Cognitive network of PD-MCI patients

The network of PD-MCI was characterized by 14 nodes and 32 edges, displaying a sparsity value of 0.41 (Fig. 1; see Table 3 for partial correlation values).

Demographic factors such as biological sex, age, and education appear to play a more marginal role in cognitive test performance within the PD-MCI cohort, losing significance in the centrality indices (especially betweenness).

Regarding MoCA, its centrality in the network of PD-MCI patients is confirmed, displaying high centrality indices. MoCA has ten connections, eight of which are positive with a slight-to-medium connection strength, and two negative ones with TMT-B-A and a small edge with age.

Considering the tests of specific cognitive abilities, the NA detects differences compared to the PD-CU network. First, the RAVLT-IR and Semantic Fluency tests lose their centrality in the PD-MCI network. Conversely, a second difference involves the reinforcement of certain connections. Specifically, TMT B-A and LOJ show higher centrality indices for both betweenness and strength.

Discussion

This is the first study using NA to compare cognitive function relationships between PD-CU and PD-MCI patients. The only previous study using NA in the context of PD compared the cognitive systems of de novo PD patients and HC, drawing data from the PPMI database and focusing on a limited number of tests and cognitive domains[21].

In interpreting NA results, the analysis of topography and centrality indices sheds light on the role of demographic variables, MoCA, and other cognitive tests within the networks.

First, the role of demographic variables was evaluated. In PD-CUs, NA revealed a relatively central role for these variables, particularly biological sex, with good centrality indices. This outcome suggests that cognitive performance is influenced by demographic factors such as biological sex, age, and education, underscoring the importance of normative data to properly standardize cognitive tests. However, this influence is reduced in the PD-MCI network. Indeed, in these cases demographic information loses much of its impact on cognitive tests, resulting in lower and less intense correlations, and generally a less central role. This is in line with findings from Tosi et al. (2020)[22]and Ferguson and Foley (2023)[21] supporting the hypothesis that cognitive decline may overshadow the influence of demographic variables. Both age and education are nodes in the networks, and they show statistically significant differences between the groups, with the PD-MCI group being older and having fewer years of education. However, these differences do not affect the networks. This is because the network analysis is based on a correlational method, which is not particularly sensitive to average differences. If age and education do influence the results, this will be evident through their connections to the cognitive tests (or nodes) they impact. However, no differences in the relationships between age, education, and the other nodes in the networks were found when comparing PD-CU and PD-MCI.

Once the role of demographic variables in the networks was clarified, the relationships between MoCA and other tests were examined. MoCA aims to assess the global cognitive functioning of patients across different

a) PD-CU	MoCA	Digit.Bw	RAVLT.IR	ROCF.C	ROCF.DR	Ekman	Stroop	TMT.B.A	Act.Naming	Sem.Flu	LOJ	Age	Sex	Edu
MoCA	1	0.460	0.637	0.200	0.236	0.352	−0.154	−0.394	0.434	0.506	0.278	−0.387	0.062	0.419
Digit.Bw	0.196	1	0.214	0.082	0.084	0.182	−0.168	−0.353	0.217	0.341	0.377	−0.241	−0.130	0.386
RAVLT.IR	0.396	0	1	0.177	0.167	0.391	-0.159	−0.334	0.328	0.408	0.141	−0.513	0.234	0.296
ROCF.C	0.050	0	0.002	1	0.124	0.157	−0.100	−0.087	0.169	0.129	0.104	−0.223	−0.025	0.076
ROCF.DR	0.041	0	0	0.020	1	0.210	0.003	−0.196	0.208	0.266	0.134	−0.202	−0.022	0.114
Ekman	0	0	0.060	0.006	0.039	1	−0.082	−0.402	0.402	0.343	0.137	−0.450	0.231	0.158
Stroop	0	−0.026	0	0	0	0	1	0.200	−0.089	−0.194	−0.147	0.253	0.020	−0.149
TMT.B.A	−0.081	−0.125	-0.033	0	-0.033	−0.200	0.060	1	−0.236	−0.388	−0.247	0.287	−0.061	−0.279
Act.Naming	0.158	0	0	0.035	0.043	0.204	0	0	1	0.370	0.233	-0.289	−0.047	0.321
Sem.Flu	0.189	0.041	0.068	0	0.102	0.069	−0.038	−0.129	0.100	1	0.338	−0.342	−0.130	0.291
LOJ	0	0.187	0	0	0	0	−0.015	−0.033	0.040	0.131	1	−0.215	−0.298	0.327
Age	−0.011	−0.002	−0.274	−0.100	−0.036	−0.227	0.123	0.007	−0.013	−0.060	−0.047	1	−0.118	−0.142
Sex	0	0	0.161	0	0	0.142	0	0	0	−0.065	−0.200	0	1	−0.244
Edu	0.148	0.149	0.044	0	0	0	−0.015	−0.053	0.113	0	0.102	0	−0.158	1
b) PD-MCI	**MoCA**	**Digit.Bw**	**RAVLT.IR**	**ROCF.C**	**ROCF.DR**	**Ekman**	**Stroop**	**TMT.B.A**	**Act.Naming**	**Sem.Flu**	**LOJ**	**Age**	**Sex**	**Edu**
MoCA	1	0.212	0.433	0.322	0.167	0.355	0.098	−0.521	0.405	0.484	0.470	−0.348	0.009	0.420
Digit.Bw	0.033	1	0.191	0.172	−0.074	0.121	0.007	−0.244	0.127	0.135	0.115	−0.141	−0.113	0.175
RAVLT.IR	0.146	0.019	1	0.332	0.106	0.253	−0.032	−0.408	0.012	0.349	0.108	−0.429	0.082	0.274
ROCF.C	0.040	0.011	0.094	1	0.173	0.214	−0.139	−0.337	0.169	0.252	0.268	−0.330	0.007	0.316
ROCF.DR	0	0	0	0.020	1	-0.006	0.060	−0.216	0.054	0.186	0.248	−0.131	−0.172	0.158
Ekman	0.088	0	0.033	0.007	0	1	0.040	−0.213	0.329	0.316	0.300	−0.232	0.206	0.324
Stroop	0	0	0	-0.015	0	0	1	0.108	-0.099	-0.081	−0.024	−0.024	−0.048	0.042
TMT.B.A	−0.219	-0.087	-0.111	-0.089	-0.054	0	0	1	-0.224	-0.417	−0.309	0.374	0.0418	−0.332
Act.Naming	0.098	0	0	0	0	0.138	0	0	1	0.300	0.585	0.068	−0.205	0.283
Sem.Flu	0.188	0	0.076	0	0.021	0.100	0	−0.134	0.022	1	0.361	−0.317	−0.208	0.172
LOJ	0.169	0	0	0.055	0.084	0	0	-0.020	0.382	0.085	1	−0.145	−0.360	0.270
Age	−0.053	0	−0.213	−0.117	0	−0.040	0	0.113	0.033	−0.068	0	1	−0.076	−0.085
Sex	0	0	0	0	−0.019	0.129	0	0	0	−0.054	−0.205	0	1	−0.041
Edu	0.169	0.019	0.026	0.115	0	0.120	0	−0.067	0.051	0	0.010	0	0	1

Table 3. Correlation between *nodes* of the PD-CU (a) and the PD-MCI (b) networks. Below the diagonal there are the Pearson's correlations, above the diagonal there are the regularized partial correlations. The values for the PD-CU group are in the first table, while those for the PD-MCI group are in the second one.

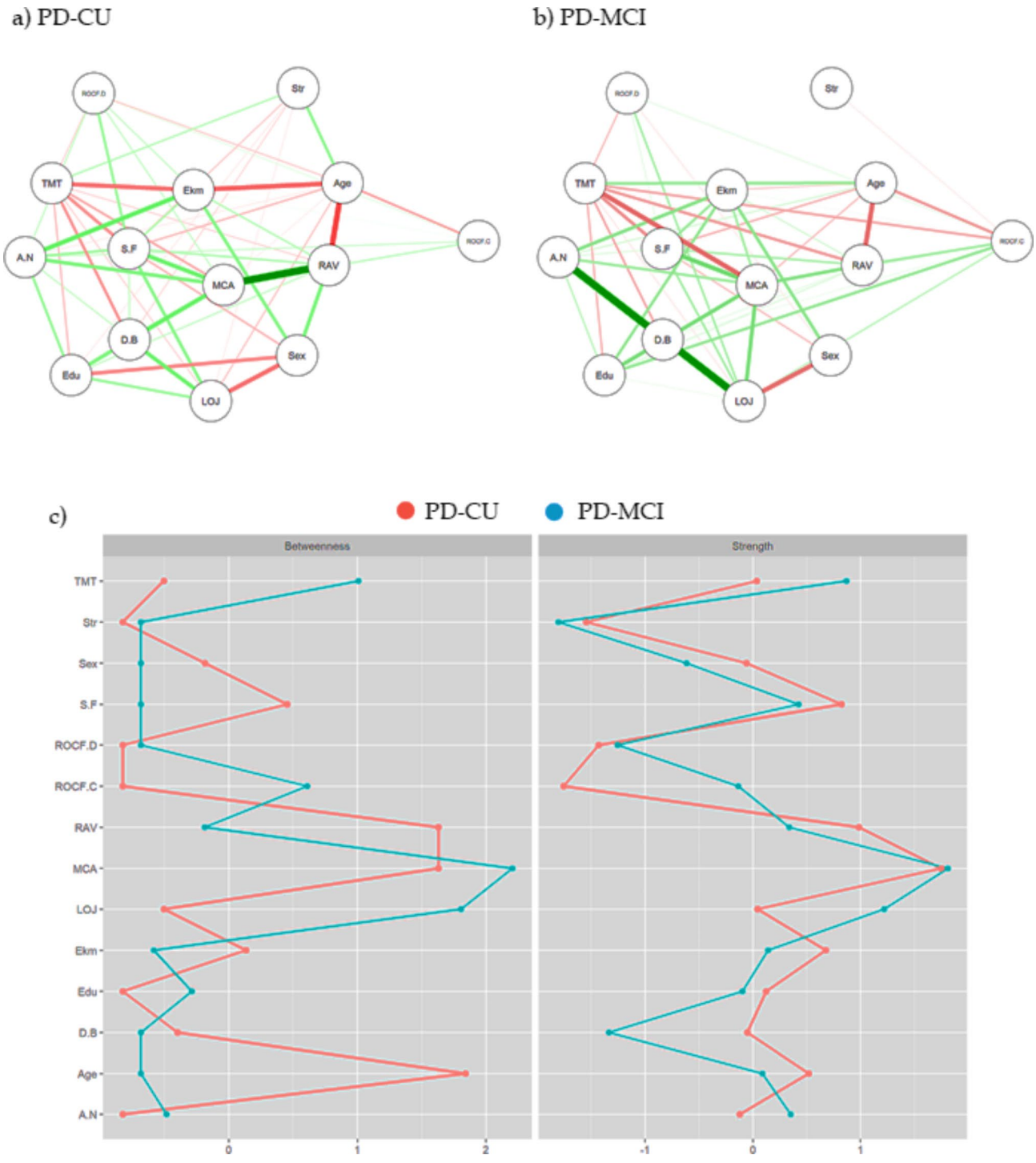

Fig. 1. Cognitive networks and their respective centrality indices. a-b) PD-CU and PD-MCI networks. In green, the regularized partial positive correlations, and in red, the negative ones. c) Betweenness and strength of the tests divided by group; in red PD-CU and in blue PD-MCI. Legend: TMT=Trail Making Test part B; Str=Stroop test (time parameter); S.F.=Semantic Fluency; ROCF.D=ROCF Delayed Recall; ROCF.C= ROCF Copy; RAV=Immediate Recall of RAVLT; MCA=MoCA; LOJ=Line Orientation Judgment; Ekm=Ekman test; Edu=Education; D.B.=Digit Backward span test; A.N.=Action Naming test.

cognitive domains. NA revealed that in both PD-CU and PD-MCI, MoCA occupies a central position in the network, showing several correlations with other tests. This highlights the suitability of MoCA as a screening test, effectively capturing global cognitive functioning in a broad and nonspecific way.

However, differences emerged between the two networks, extending beyond demographic variables. A notable initial difference concerns the reduced centrality of the RAVLT-IR and the Semantic Fluency test in the

PD-MCI network. The RAVLT-IR is a verbal learning test that requires both memory and executive abilities, whereas Semantic Fluency is a test of lexical access based on semantic keys. The Semantic Verbal Fluency test has been previously identified as a predictor of conversion from mild cognitive impairment to dementia[42]. In this context, our results are particularly interesting as they are similar to network analysis studies in patients with Alzheimer's disease (AD)[21,22,23]. For example, Tosi et al. (2020)[22]used network analysis on AD, vascular dementia, and healthy controls, confirming the central role of semantic fluency in AD. This suggests that semantic fluency may play a role in cognitive reorganization processes in neurodegenerative diseases such as AD. Although this is a reliable finding for AD patients, it does not hold the same validity for patients with PD, whose "classic" phenotype is a dysexecutive syndrome. However, patients with PD-MCI perform worse on Semantic Fluency than PD-CU patients and HC[43,44]. Not only are PD patients with semantic fluency deficits more susceptible to dementia than those without these deficits[45], but they also report a poorer quality of life and increased carer burden[44]. Furthermore, a recent study analysing brain activation during Semantic Fluency in PD patients found that those with MCI had increased activity in the right angular gyrus[46], supporting the presence of an early compensatory reorganization mechanism.

The network analysis revealed not only a reduction in connections but also some reinforcements, which represent the second difference between the networks. Specifically, the results showed that in PD-MCI patients, the TMT B-A and LOJ tests are more central within the network. TMT B-A reflects attentional and executive functions, while LOJ assesses visuo-spatial abilities. According to the dual syndrome hypothesis[47], cognitive deficits in PD can reflect either an anterior dysfunction due to dopaminergic loss, leading to attentional and executive deficits, or a posterior dysfunction with visuo-spatial deficits due to cholinergic loss. Patients with posterior phenotype are at higher risk of developing PD dementia[48]. In this context, our results support the importance of these tests assessing PD patients, being central in the reorganization of the cognitive system.

It is interesting to note that, apart from TMT B-A, the results do not show other executive tests as central in the networks. On the one hand, it is possible that TMT-B-A explains most of the variance due to executive functions, thus leaving (after partialization) little variance to be explained by the other executive functions tests. Another possibility is that, after partialization, executive functions tests capture independent facets, and those related to the TMT B-A (i.e., switching, fast processing) are more relevant during the reorganization process.

Some limitations of our study must be acknowledged. First, the use of a cognitive battery that was unbalanced across domains (with only one test for social cognition) limited our ability to thoroughly analyse the relationships between the cognitive domains most affected in PD. Future studies should therefore consider including the five cognitive domains recommended by the MDS, along with the social cognition domain. Second, the cross-sectional experimental design needs caution in inferring individual patient functioning, both in terms of the cognitive system dynamics (i.e., relationships between tests) and in rehabilitation implications. Cross-sectional designs cannot establish causality, which longitudinal designs could address. Thus, future studies should consider a within-subject longitudinal design to delve deeper into cognitive functioning and its temporal evolution. Lastly, neuroimaging data are lacking; however, the focus of this study was on the functional relationships between tests rather than correlating tests with specific cortical areas or subcortical bundles.

Despite these limitations, this study offers a new perspective on the cognitive deficits field in PD. Network analysis allows to move beyond the simple dichotomy of intact/impaired, enabling a deeper understanding of the changes in cognitive organization in PD patients with cognitive decline. This new perspective is extremely valuable both for the clinical neuropsychologist, who needs to detect the cognitive profile of patients, and for the researcher, who aims to better understand the architectural changes in cognitive decline. Lastly, a better understanding of the mechanisms underlying cognitive decline can significantly impact both the diagnostic process and subsequent cognitive treatment.

Data availability

The data will be available upon reasons to the corresponding authors.

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Author contributions

C.L. conceptualized the study, curated the data, conducted investigations, administered the project, and drafted the original manuscript. D.L.R. contributed to conceptualization, conducted formal analyses, designed methodologies, and contributed to the draft of the original manuscript. M.C.M. and R.B. provided resources for the study. C.P. contributed to conceptualization, guided methodology implementation, and supervised the study. All authors critically reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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