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ADVANCES IN NEURODEGENERATIVE AND PSYCHIATRIC IMAGING SPECIAL FEATURE: REVIEW ARTICLE

Towards understanding neural network signatures of motor skill learning in Parkinson's disease and healthy aging

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ABSTRACT

In the past decade, neurorehabilitation has been shown to be an effective therapeutic supplement for patients with Parkinson's disease (PD). However, patients still experience severe problems with the consolidation of learned motor skills. Knowledge on the neural correlates underlying this process is thus essential to optimize rehabilitation for PD. This review investigates the existing studies on neural network connectivity changes in relation to motor learning in healthy aging and PD and critically evaluates the imaging methods used from a methodological point of view. The results indicate that despite neurodegeneration there is still potential to modify connectivity within and between motor and cognitive networks in response to motor training, although these alterations largely bypass the most affected regions in PD. However, so far training-related changes are inferred and possible relationships are not substantiated by brain-behavior correlations. Furthermore, the studies included suffer from many methodological drawbacks. This review also highlights the potential for using neural network measures as predictors for the response to rehabilitation, mainly based on work in young healthy adults. We speculate that future approaches, including graph theory and multimodal neuroimaging, may be more sensitive than brain activation patterns and model-based connectivity maps to capture the effects of motor learning. Overall, this review suggests that methodological developments in neuroimaging will eventually provide more detailed knowledge on how neural networks are modified by training, thereby paving the way for optimized neurorehabilitation for patients.

INTRODUCTION

Parkinson's disease (PD) is a multisystem neurodegenerative disorder affecting mainly the basal ganglia leading to a range of motor and non-motor symptoms.¹ Several studies have shown that PD patients display altered brain connectivity patterns compared to healthy elderly, which underlies some of their motor symptoms.²⁻⁵ Patients typically display a disconnection of the striato-supplementary motor area (SMA) pathway that likely contributes to their bradykinesia,^{3,6} while tremor may be the result of a pathological interaction between the basal ganglia and the cerebellothalamic circuit.^{3,7,8} PD patients also show altered resting state connectivity in the subthalamic nucleus network (STN) while on their medication, displaying, *e.g.* attenuated coupling between the STN and key executive regions compared to controls,⁹ as well as in the striatofrontal pathways, particularly in patients with freezing of gait.² Dopaminergic treatment alleviates symptoms and

reinstates some degree of sensorimotor control,^{10,11} as well as partially normalizes neural connectivity patterns.^{2,4,12,13} Nevertheless, treatment effects fade with time, requiring supplementary therapies. Over the past few years, evidence has emerged that neurorehabilitation can reduce functional disability and improve mobility in PD.¹⁴⁻¹⁶ We define neurorehabilitation as motor learning or other modes of training aimed to instigate functional improvements after neural injury and/or long-term neurological damage. The influence of rehabilitation on non-motor symptoms, such as depression, apathy or anxiety, is currently less clear for PD and requires further investigation.^{17,18} Hence, for this review, we focus on motor learning and its influence on motor performance only.

Motor learning is defined as the acquisition and optimization of a series of inter-related movements, resulting in more accurate and efficient performance.¹⁹ Consolidated motor

learning is characterized by three crucial components: (i) transfer to untrained tasks; (ii) resistance to distraction, *i.e.* automatization; and (iii) retention after a period without practice.^{20,21} An important distinction exists between short- and long-term training studies. The former consist of a single training session, sometimes followed by a 24h-retention measurement (offline consolidation). The latter includes multiple training sessions over a period of weeks. In young healthy adults, it was shown that during sustained motor learning a shift in activation occurs from the anterior to posterior striatum with time, indicating consolidation of learning.²² Due to dopamine depletion, people with PD experience dysfunction of various regions within the striatum, whereby the posterior striatum is particularly affected in contrast to the relatively spared anterior striatum.²³ This would explain why people with PD continue to display difficulties with motor memory consolidation and especially with retention of practice effects, while initial learning is preserved.^{24–27} To compensate for the loss of the posterior striatum, PD patients rely more on anterior circuits.²⁸ Hence, behavioral data can show improvements indicating consolidation, whilst PD patients may still utilize attentional circuits to boost performance. Therefore, brain-behavior outcomes are indispensable to distinguish this "pseudo consolidation," thus allowing to check against the "normal" or near-normal shifts of recruitment inherent to consolidation. Although recent work revealed that motor learning can trigger plasticity-related changes in brain activation and connectivity in PD patients,^{29–34} there is a great heterogeneity in PD in terms of disease and symptom severity. As a result not all patients respond similarly to training programs,^{25,35,36} highlighting a need for adequate neural circuit-based predictors of motor learning to forecast the effects of neurorehabilitation.

Over the past years, many task-based neuroimaging studies have been conducted which focused on identifying the locality of the BOLD-response changes as a result of motor learning. Yet, interpretation of these studies was hampered by several difficulties: (i) lack of control groups with placebo interventions³⁷; (ii) learning-related changes in performance, clouding a clear understanding of the neural correlates; (iii) lack of comparability of difficulty level of learning tasks amongst groups; and (iv) lack of statistical power. This, together with methodological developments in the field of neuroimaging, formed the impetus to shift the focus from examining brain activation patterns towards studying connectivity between brain regions, *i.e.* either (i) anatomical connectivity, a pattern of anatomical links between areas; (ii) functional connectivity, a pattern of statistical dependencies between regions; or (iii) effective connectivity, the causal interactions between regions. With these developments in network analysis, the enormous complexity of the human brain is currently being mapped in both health and disease, including PD. This intricacy is challenged even further when time-dependent interventions need to be captured on top of the baseline status, as is the case in neurorehabilitation studies.

The current review has three aims. First, it will provide an overview of the known changes in neural networks involved in motor learning in healthy elderly adults and PD patients and identify the methodological weaknesses of current approaches. Second, it

will explore whether connectivity patterns could serve as predictors for therapy response. Finally, we will discuss and propose future directions on how to use brain imaging to further the field of neurorehabilitation.

METHODOLOGICAL APPROACH TO THIS REVIEW

For our primary aim, we performed a PubMed search looking into motor-learning related connectivity changes in both healthy aging and PD. For our exploratory question, we additionally selected studies using connectivity to predict training-related effects involving mostly young healthy subjects. We combined motor-learning related search terms (motor learning, motor sequence learning, consolidation, automaticity, retention, motor rehabilitation or exercise therapy) with the term "connectivity" and either "Parkinson's disease," "aging" or "predict(ion)" (see Supplementary Table 1). We only included papers that: (i) included either functional or effective connectivity; (ii) included at least a baseline and post-training task-based or resting-state MRI or magnetoencephalography/electroencephalography (MEG/EEG) measurement; (iii) concerned a motor training intervention and not speech therapy, cognitive training or motor adaptation; (iv) involved either short- or long-term training; and (v) included a minimum of 10 subjects in each group. We excluded studies performed in animals and did not include studies on changes in anatomical connectivity as a result of motor training due to a current lack thereof.

The literature search resulted in 319 articles, of which 12 papers studying changes in connectivity in relation to motor learning or other forms of motor training were selected. After screening of references and citations, four more papers were included. Overall, the selection included five papers on aging, five papers on PD and six on prediction. For an overview, see [Figure 1](#).

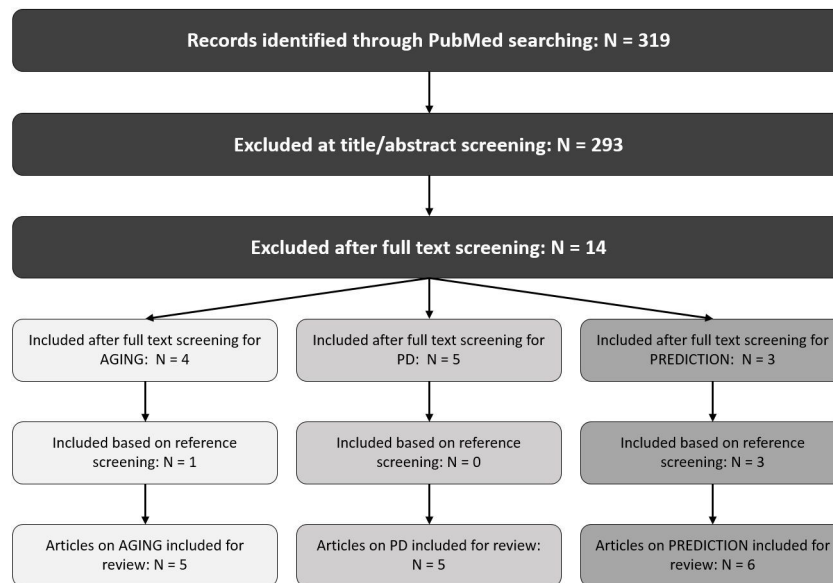
EFFECTS OF MOTOR LEARNING ON CONNECTIVITY

For our main question, we included five articles in healthy elderly adults and five in PD ([Figure 1](#)).

Healthy elderly adults

In healthy adults, two motor learning studies were found ([Table 1A](#)), both while in resting state, though one using MEG³⁹ and the other MRI.³⁸ Although the studies looked at different types of tasks, *i.e.* finger tapping³⁹ and bimanual tracking,³⁸ both found a differential pattern of changes in resting-state sensorimotor connectivity as a result of short-term training: while connectivity increased in young adults, decreases were detected in older adults.^{38,39} The authors hypothesized that the age-related decrease in within-network connectivity was an indirect result of increased interactions between the motor network and other networks as a compensatory strategy to optimize task performance.^{38,40} Brain-behavior correlation analysis further showed differences between young and older adults. While faster learning was associated with increased connectivity between primary sensorimotor cortex and the SMA in young adults, it was related to decreased connectivity in older adults ([Table 2A](#)).³⁹ The increased connectivity in young adults was therefore interpreted as facilitating motor learning. In older

Figure 1. Overview of the literature search.



adults, faster learning was associated with a decreased necessity for compensatory circuits.³⁹

Solesio-Jofre et al further investigated changes after 2 weeks of bimanual tracking practice, revealing no age-related modulations of long-term practice.³⁸ Both groups increased resting-state connectivity within the right hemisphere, possibly reflecting greater interactions amongst motor areas to control the less skilled non-dominant hand in this bimanual task.

In addition, one short-term⁴¹ and two long-term^{42,43} studies investigated the influence of aerobic exercise on functional connectivity using resting state fMRI. Weng et al showed that a single session of 30 min of aerobic exercise enhanced the integration of attention and executive networks in both young and older adults compared to passive exercise.⁴¹ However, the increase in functional connectivity was greater in older adults, suggesting a restoration of connections that decreased with aging.⁴¹ On the long-term (≥ 12 weeks), similar increases in functional connectivity within the default mode network (DMN) and between the DMN and sensorimotor network were found in healthy elderly.^{42,43} McGregor et al further showed that these changes were associated with improved motor performance.⁴³ While these studies did not incorporate motor learning *per se*, it was shown that aerobic exercise can boost motor learning capacities in both older people and PD patients.^{29,44} This would argue in favor of investigating the combined effects of aerobic exercise and motor learning on neural networks in the future.

People with Parkinson's disease

People with PD show alterations in neural network connections compared to healthy controls during performance of motor tasks of different complexities.^{2,3,5} In brief, strengthened corticocerebellar connectivity, increased connections between the anterior putamen and cortical motor regions and increased connectivity of the sensorimotor network with the attentional networks were found. These abnormalities have been suggested to signify

top-down compensatory motor control patterns to overcome altered motor automaticity in the affected posterior corticostriatal circuits.

As for motor learning of finger sequences, a short-term task-based fMRI study by Wu et al revealed that PD patients OFF medication and healthy elderly controls used different brain networks to achieve automaticity of the task (Tables 1B and 2B).³³ In healthy elderly, reaching automaticity was accompanied by strengthening connectivity within the motor network, specifically with the posterior putamen, in combination with a decreased involvement of the attentional networks. Though PD patients were able to reach a degree of automaticity, they displayed a sustained need for attentional control. Connectivity within the motor network also did not increase to a similar extent as in healthy elderly. In a long-term task-based fMRI study, Wu et al further investigated the influence of attention on learning to automatically perform finger movements, practiced over several days (Tables 1B and 2B).³⁴ After learning and unlike controls, PD patients showed continued connectivity with the dorsolateral prefrontal cortex of the attention network. Interestingly, connectivity with the posterior putamen did not increase in PD, underscoring the significance of basal ganglia dysfunction for automaticity deficits. Once automaticity was achieved, all participants were asked to reattend to the task. While this affected the global attentional and cortical motor networks of patients and controls similarly, this was not the case for the striatal connections. In healthy elderly, the striatal connections remained stable. In PD, however, connectivity from both anterior and posterior putamen to the primary motor cortex decreased inducing a shift back from the automatic to attention controlled mode.

More recently, Manuel et al looked into short-term changes in resting-state connectivity using EEG after practicing mirror drawing, a task appealing more to sensory integration than Wu et al's paradigms (Table 1B).⁴⁵ Also, contrary to the studies by Wu et al, this study tested patients ON medication. They found

Table 1. Studies on brain connectivity changes as a result of motor learning in healthy aging and Parkinson's disease

| Author | Participants | Design | Task & Training | Training intensity | Imaging method | Connectivity measure |
|--|---|--------------|--|--|--------------------------------|--|
| A. Aging | | | | | | |
| Mary <i>et al.</i> 2017 ³⁸ | 14 YA 14 OA | Case-control | <u>Task & training:</u> Finger tapping | Short-term: 70 trials in learning phase + 50 trials in retest phase | rsMEG | Seed-based correlation |
| Solesio-Jofre <i>et al.</i> 2018 ³⁹ | 23 YA 21 OA | Case-control | <u>Task & training:</u> Bimanual tracking | Short-term: 144 trials across six runs Long-term: 1 h/day, 5x/2 weeks | rsMRI | Seed-based correlation |
| Weng <i>et al.</i> 2016 ⁴⁰ | 12 YA 13 OA | Case-control | <u>Task:</u> / <u>Training:</u> Active OR passive cycling | Short-term: 30 min | rsMRI | Seed-based correlation based on gICA |
| Flodin <i>et al.</i> 2017 ⁴¹ | 22 OA aerobic 25 OA stretch | RCT | <u>Task:</u> / <u>Training:</u> Aerobic exercise OR stretching and toning | Long-term: 30–60 min/day, 3x/week for 6 months | rsMRI | Seed-based correlation + Graph theory + ICA + NBS+MVPA |
| McGregor <i>et al.</i> 2018 ⁴² | 19 OA aerobic 18 OA balance | RCT | <u>Task:</u> / <u>Training:</u> aerobic spin intervention OR balance/strength training | Long-term: 20–45 min/day, 3x/week for 12 week | rsMRI | Seed-based correlation |
| B. Parkinson's disease | | | | | | |
| Wu <i>et al.</i> 2010 ³³ | 12 OA 12 PD-OFF | Case-control | <u>Task & training:</u> Finger tapping | Short-term: Until performed from memory 10 times in a row without error | Task-based fMRI | PPI |
| Wu <i>et al.</i> 2015 ³⁴ | 22 OA 22 PD-OFF | Case-control | <u>Task & training:</u> Visuomotor association | Long-term: 30 min x 4/day, until reaching automaticity (max 5 days) | Task-based fMRI | Granger causality |
| Shah <i>et al.</i> 2016 ⁴³ | 27 PD-OFF: 14 voluntary 13 forced | RCT | <u>Tasks:</u> continuous fingertip force tracking task & finger tapping <u>Training:</u> Cycling at voluntary OR forced speed | Long-term: 1 h/day, 3x/week, for 8 weeks | Task-based fMRI fcMRI rsMRI | Seed-based correlation |
| Nackaerts <i>et al.</i> 2018 ⁴⁴ | 27 PD-ON: 13 writing 14 stretch | RCT | <u>Task:</u> Writing <u>Training:</u> Writing OR stretch (placebo) | Long-term: 30 min/day, 5x/week, for 6 weeks | Task-based fMRI | DCM |
| Manuel <i>et al.</i> 2018 ⁴⁵ | 10 OA 9 PD-ON | Case-control | <u>Task & training:</u> Mirror drawing | Short-term: four trials on day 1 and 4 trials on day 2 | rsEEG | Imaginary coherence |

DCM = dynamic causal modeling; EEG = electroencephalography; MEG = magnetoencephalography; MVPA = multivariate pattern analysis; NBS = network based statistics; OA = older adults; PD = Parkinson's disease; PPI = psychophysiological interactions; RCT = randomized controlled trial; YA = young adults; (f)MRI = (functional) magnetic resonance imaging; fcMRI = MRI, during which the subject stimulus is constant throughout the entire acquisition⁴³; (g)ICA = (group) independent component analysis; rs = resting state.

increased connectivity of the left parietal cortex with the rest of the cortex in PD compared to healthy elderly, suggesting that learning induced a greater reliance on sensory integration. However, this increased connectivity of the left parietal cortex immediately after learning was associated with worse offline consolidation 24 h later (Table 2B). Although increased

connectivity allowed patients to achieve similar initial learning, using these compensatory circuits likely prevented subsequent consolidation of the motor trace.

Only two connectivity studies looked into the effects of long-term motor training in PD, involving several weeks of practice

Table 2. Key findings and interpretation

| Author | Key findings | Brain-behavior relation |
|--|---|--|
| A. Aging | | |
| Mary <i>et al.</i> 2017 ³⁸ | In YA short-term rsFC of sensorimotor network increased, while it decreased in OA | <ul style="list-style-type: none"> In YA faster learning was correlated with increased post-training rsFC with the SMA, while the opposite was observed in OA Post-training changes in rsFC were correlated with offline improvement in both YA & OA |
| Solesio-Jofre <i>et al.</i> 2018 ³⁹ | <ul style="list-style-type: none"> In YA short-term rsFC of sensorimotor network increased, while it decreased in OA Both YA & OA exhibited increased sensorimotor-related long-term rsFC changes | Increases in the inter hemispheric connection strength across the 2 week period were correlated with greater motor improvement in both YA & OA |
| Weng <i>et al.</i> 2016 ⁴⁰ | Aerobic exercise increases the integration of attention and executive control networks in YA and OA, although with greater increases in OA | Not applicable |
| Flodin <i>et al.</i> 2017 ⁴¹ | There was no differences between groups in resting state network connectivity changes from baseline to post-training | Across groups, post-intervention increases in DMN and sensorimotor network connectivity were related to aerobic capacity improvements |
| McGregor <i>et al.</i> 2018 ⁴² | Aerobic exercise training increased connectivity between primary motor cortex and DMN compared to balance training | The increase in connectivity correlated with improved motor performance |
| B. Parkinson's disease | | |
| Wu <i>et al.</i> 2010 ³³ | <ul style="list-style-type: none"> In OA automaticity is accompanied by strengthened connectivity in sensorimotor networks, which is less so in PD Attentional networks became less necessary in OA in automatic stage, while they remained active in PD | Not applicable |
| Wu <i>et al.</i> 2015 ³⁴ | <ul style="list-style-type: none"> Attentional networks became less necessary in OA in automatic stage, while they remained active in PD Re-attending to the task resulted in a shift back from automatic to controlled mode in the striatum in PD, but not in OA | Not applicable |
| Shah <i>et al.</i> 2016 ⁴³ | Patients who pedaled faster had increased cortico-subcortical connectivity during task performance | A positive correlation was found between pedaling rate and change in FC from the most affected M1 to the ipsilateral thalamus |
| Nackaerts <i>et al.</i> 2018 ⁴⁴ | Writing training enhanced communication in the left visuomotor integration system compared to placebo | No significant correlations between behavioral and connectivity parameters were found |
| Manuel <i>et al.</i> 2018 ⁴⁵ | PD patients exhibited increased rsFC of the left parietal cortex with the rest of the cortex compared to OA | A lower FC of the left parietal cortex with the rest of the cortex correlated with greater offline consolidation gains across both groups |

CMA = cingulate motor area; DMN = default mode network; FC = functional connectivity; OA = older adults; PD = Parkinson's disease; rs = resting state; SMA = supplementary motor area; UPDRS = Unified Parkinson's Disease Rating Scale; YA = young adults

(Table 1B). Shah *et al.* studied the effects of 8 weeks of cycling, comparing a voluntary and forced exercise program in a randomized design, using fMRI with a continuous task.⁴⁶ However, due to a lack of difference between both groups for pedaling rate, a direct correlation between pedaling rate and connectivity was made, rather than comparing both groups. It was found that patients who pedaled faster, increased their connectivity between the most affected M1 and thalamus during finger tapping (Table 2B). Importantly, this effect was sustained after 4 weeks without practice indicating good retention. Nackaerts *et al.* looked into motor learning of handwriting while patients were tested and trained ON medication.⁴⁷ They compared a group that received 6 weeks of intensive handwriting training with a

placebo training of stretch and relaxation exercises in a randomized design. Task-based fMRI results revealed an increase in connectivity targeting the SMA by means of enhanced visuoparietal coupling, suggesting more efficient communication in the left visuomotor integration system after real training, rather than sham. As correlations between connectivity changes and behavioral improvements outside the scanner were not significant, a firm interpretation of these findings was not possible.

Overall, the above suggests that motor learning associated increases of connectivity remain largely similar in healthy aging and that also in PD motor network communication is capable of modification, albeit to a lesser extent. Nevertheless,

Box 1: Analysis methods used to study motor learning-related changes in brain connectivity

| | |
|---|--|
| Correlation analysis = model-based method to correlate the time course of a seed region and that of any other brain area | |
| Advantages | Drawbacks |
| <ul style="list-style-type: none"> – Easy to implement – Minimal number of assumptions | <ul style="list-style-type: none"> – No inference on directionality |
| Coherence analysis = model-based method that quantifies how well one signal can be represented by a linear transformation of another | |
| Advantages | Drawbacks |
| <ul style="list-style-type: none"> – Insensitive to regional differences in blood flow and volume | <ul style="list-style-type: none"> – No inference on directionality |
| Psychophysiological Interactions = model-based linear regression method to assess how activity in one region predicts/explains activity of another | |
| Advantages | Drawbacks |
| <ul style="list-style-type: none"> – Easy to implement | <ul style="list-style-type: none"> – No inference on directionality |
| Dynamic Causal Modeling = model-based method to infer hidden neuronal states from measurements of brain activity using a Bayesian framework | |
| Advantages | Drawbacks |
| <ul style="list-style-type: none"> – Allows inference on directionality – Tight coupling to biophysical models | <ul style="list-style-type: none"> – Only a limited number of regions of interest – Direction of connections needs to be pre-specified |
| Granger Causality = data-driven method to map connectivity using vector autoregressive modeling of fMRI time series | |
| Advantages | Drawbacks |
| <ul style="list-style-type: none"> – Allows inference on directionality – No need to pre-specify the direction of connections | <ul style="list-style-type: none"> – Requires relatively short repetition time for fMRI |

training-related alterations in PD mainly involve strengthening of attentional and sensory-motor compensatory circuits rather than achieving increased efficiency of motor automaticity related cortical-subcortical network connections, as such bypassing the affected regions and in particular the posterior putamen.

METHODOLOGICAL CHALLENGES

As can be seen in Table 1, most studies so far had uncontrolled designs, used variable durations of training and task-paradigms and involved relatively small sample sizes. Not only is it difficult to recruit large numbers of patients in the field of neurorehabilitation, neuroimaging studies in PD also suffer from a severe loss of data due to head motion artefacts during scanning. In the studies described above this was up to 15%,^{34,47} while this factor is often not taken into account when calculating the required sample size.

The studies described above highlight three major challenges. First, mainly model-based analysis methods were used (Table 1). Box 1 summarizes the advantages and drawbacks of the used methods. In model-based approaches, a region of interest (ROI) is selected as a seed based on prior knowledge and a connectivity map is created between the seed region and the rest of the brain or other selected ROIs. The advantage is that these techniques are easy to implement and straightforward to interpret. However, strong prior knowledge on the possible underlying neural processes is required,⁴⁸ as the choice of seed region has a crucial effect on the changes in the connectivity pattern likely to be observed.⁴⁹ Finally, it is possible that interesting changes in

connectivity were missed simply because the connection or ROI is not included.

Second, four out of five PD studies used task-based measurements (Table 1B). The challenge in these studies is that it is important to obtain a similar performance, not only between groups, but also across sessions, as otherwise the observed neural changes could have been due to performance differences instead of motor learning.⁵⁰ In other words, if performance is kept constant, but neural changes are observed after training, these neural changes are likely associated with learning-related plasticity. The study by Nackaerts *et al*,⁴⁷ *e.g.* found similar performance at baseline and after training in the scanner thus making a clean interpretation of motor learning effects possible. Outside the scanner, though, motor gains were apparent after training. Both studies of Wu *et al* showed changes in performance from early learning to the automatic stage, though this did not differ between patients and healthy controls.^{33,34} Shah *et al* did not report the direct comparison of behavioral results between groups or time points.⁴⁶

A third and final point is the influence of dopaminergic medication. Research has shown that dopaminergic medication, at least partially, normalizes neural networks in PD in the resting-state^{12,13} and during tasks.^{51–53} Hence, for research purposes it has been recommended to perform neuroimaging while patients are OFF medication.⁵⁴ This was the case in three out of five studies (Table 1B).^{33,34,46} Though connectivity measured while OFF medication might be more sensitive to

detect motor learning-related changes, this does not reflect daily life situations in which the training will occur. Also, it cannot be assumed that practicing while ON medication generalizes to OFF medication and vice versa.⁵⁵ This specifically might have influenced the study by Shah et al as there was an incongruence between testing (OFF) and training state (ON).⁴⁶ So far, only two studies described the effects of motor learning on connectivity patterns while ON medication,^{45,47} demonstrating a need to replicate and extend these findings.

PREDICTING MOTOR LEARNING CAPACITY USING CONNECTIVITY

PD is a highly heterogeneous disorder and studies have shown a variable response to neurorehabilitation. Patients with freezing of gait respond differently to various training modalities than those without, illustrating greater difficulties with consolidation of learning effects, such as with transfer, automatization and retention.^{25,26,35,36} This warrants different and personalized training approaches pending the patient characteristics, such as setting the cognitively challenging training conditions to the patients actual level of cognitive functioning. Patients with freezing in particular experience more cognitive difficulties,⁵⁶ which might influence their motor learning capacities. Research in healthy elderly and PD patients without freezing has shown that exercise therapy can not only boost motor learning capacities,^{29,44} but also has a positive effect on non-motor symptoms such as cognition,^{57,58} thereby providing a possible dual advantage. Until now, there is a lack of evidence on whether other PD-phenotypes (e.g. tremor-dominant patients) display differential learning effects. However, behavioral work has shown that motor learning, and especially consolidation, is negatively impacted by disease progression across all patients.^{24,59} While there are no neural underpinnings to support this yet, this is likely the result of the progressive striatal denervation extending beyond the sensorimotor striatum into the associative regions. A recent behavioral study indicated that high cognitive capacity and low motor ability predicted better dual task training results.⁶⁰ As neurorehabilitation requires effort and motivation as well as professional input, predictive biomarkers for neuroplasticity have an important future role to play in allocation of individual patients to varying levels of intensity of training.

For this exploratory question, six articles were selected (Figure 1), which are summarized in Table 3. Resting-state functional connectivity, using MRI, EEG and MEG, was shown to predict short- and long-term motor learning. Studies using tasks that involved a strong visuomotor component revealed that greater connectivity between primary motor cortex, premotor cortex and parietal cortex before training predicted greater motor learning improvements, possibly reflecting a greater capacity for visuomotor integration.^{61–63} Conversely, a lower baseline connectivity between the primary sensorimotor cortex and both putamen and cerebellum were linked to greater gains of a finger tapping sequence in young adults.⁶⁴ Similarly, reduced connectivity between motor and visual areas predicted faster learning of a finger tapping task in the long term, suggesting that individuals with a greater autonomy

of visual and motor processes developed motor–motor associations faster.⁶⁵ Using a graph theory-based approach, two predictive biomarkers were uncovered to distinguish high from low learning rates.⁶⁶ While high coherence, *i.e.* the spectral analog of a correlation analysis, in the visual cortex was associated with slower learning rates, a high coherence in the parietal operculum and planum temporale was linked to higher learning increments.

At first sight, these results seem inconclusive, as motor learning was predicted by both increased and decreased connectivity at baseline. However, different types of tasks were used. The former group of studies used tasks with a strong visuomotor component, while the latter group involved finger tapping tasks. Importantly, none of these studies compared whether neural predictors indeed explained outcomes better than behavioral ones.

Based on these findings in healthy adults and the findings that connectivity patterns can predict the response to dopaminergic medication in PD,^{67,68} we speculate that connectivity measures may be of additional value to predict the response to neurorehabilitation. Two factors should be considered. First, dopaminergic medication may have differential effects depending on the learning stage, specifically in the early stages of the disease.⁶⁹ Levodopa can cause an overdose in the relatively intact anterior putamen, thereby worsening the acquisition of a motor task.^{70,71} As later stages of motor learning are more dependent on the posterior putamen,²² that is already affected early on in the disease, dopaminergic medication may be beneficial during these stages as opposed to during early learning.^{70,71} Hence, studies addressing early vs late learning may not yield the same results. Second, as mentioned above, compensatory mechanisms play an important role in PD.^{2,3,5} In healthy elderly, it has been shown that lower baseline connectivity between the sensorimotor cortex and regions involved in visual motion processing, the default mode network and dorsal attentional network are linked with better learning.⁶⁴ Hence, less pressure on cognitive resources at baseline, results in enhanced motor learning. In line, we anticipate that PD patients with greater remnants of connectivity between the posterior putamen and other motor regions and those with lower connectivity in compensatory systems, will have greater motor learning capacities. A protocol published on an ongoing study may shed light on these assumptions.⁷²

DISCUSSION—FUTURE POTENTIAL FOR BRAIN IMAGING IN NEUROREHABILITATION

Despite the methodological issues identified above, connectivity measures may be more sensitive than brain activation patterns to capture long-term motor learning, as brain regions operate in circuits rather than as single structures.⁷³ For chronic degenerative conditions such as PD, connectivity measures may be better equipped to distinguish between spontaneous compensation, inducing abnormal activity and entanglement in the brain²⁸ as well as changes induced by training. As such, several recent developments hold promise to gain a more in depth understanding of learning-related connectivity changes in PD, as described next.

Table 3. Studies on prediction of motor learning outcome based on connectivity measures

| Author | Participants | Task | Training intensity | Imaging method | Connectivity measure | Prediction method |
|---|-------------------------------------|------------------------------------|---|-----------------|------------------------|--|
| Wu <i>et al.</i> 2014 ⁶¹ | 17 YA | Pursuit rotor task | Short-term: two practice blocks of 5 min in single session | rsEEG | Coherence | Partial least squares regression model |
| Bogdanov <i>et al.</i> 2017 ⁶² | 18 YA | Cued sequence production task | Long-term: 16 sequences, 40 trials/s, 6 runs/session for 3 days | Task-based fMRI | Graph theory | New approach: combining discriminative subspace learning in network space coupled with significant conserved subgraph mining |
| Mary <i>et al.</i> 2017 ⁶³ | 14 YA 14 OA | Finger tapping task | Short-term: 1 sequence, 2x/trial for 70 trials | rsMEG | Seed-based correlation | Correlation analysis |
| Mattar <i>et al.</i> 2018 ⁶⁴ | 19 YA | Finger tapping task | Long-term: 6 sequences, 150 trials/session, 10 sessions/2 weeks for 6 weeks | rsMRI | Seed-based correlation | Correlation analysis |
| Manuel <i>et al.</i> 2018 ⁶⁵ | 24 YA: 12 learning 12 control | Drawing task | Short-term: 12 min/day, 2 days: • Learning: Mirror-drawing task • Control: same task, without mirroring of cursor | rsEEG | Imaginary coherence | Correlation analysis |
| Wu <i>et al.</i> 2018 ⁶⁶ | 32 YA | MSL task (wrist extension-flexion) | Short-term: 19-target sequence, 21 times on Day 1, 3 times on Day 2 | rsEEG | Coherence | Partial least squares regression model |

EEG = electroencephalography; MEG = magnetoencephalography; (f)MRI = (functional) magnetic resonance imaging; MSL = motor sequence learning; OA = older adults; rs = resting state; YA = young adults

Particularly, data-driven methods may play an important role as no prior knowledge on the spatial or temporal pattern is required,⁴⁸ possibly revealing important, yet unexpected, connections. The difficulty with data-driven methods is that large sample sizes are necessary to obtain sufficient power to detect changes. In the neurorehabilitation field it is difficult to recruit large numbers of patients willing to participate in long-term training, with at least two intensive task-based fMRI sessions. As mentioned above, studies in PD also suffer from a severe loss of data due to head movement, especially in task-based approaches. For this reason, it has been put forward that resting-state measurements may provide a better and more feasible paradigm.⁷⁴ As for using resting-state fMRI in the context of motor learning, it is firstly unclear whether participants are actually able to achieve a resting-state immediately following a training session. Second, wakefulness is assumed in resting-state studies. However, recent work showed that 50% of participants undergoes a transition to light sleep at least once over a duration of 10 min, which resulted in increased functional connectivity compared to wakefulness.⁷⁵ Overall, both task-based and resting-state studies will have merit when exploring the neural networks underlying neurorehabilitation in PD. The most detailed and skill-specific information will

likely come from task-based measures, especially when taking the earlier highlighted methodological difficulties of conducting a training study in the scanner into account. On the other hand, resting-state measures are better able to capture whether similar changes in connectivity patterns occur in connection with learning irrespective of task or skill set. In addition, resting-state measures have the advantage that they can be more easily acquired in large patient samples, which allows for adequate statistical power in prediction models.

In recent years, network neuroscience has also gained importance using graph theory.^{73,76,77} In this approach, a complex network is described as a collection of nodes, *i.e.* ROIs, and edges, representing the connections (anatomical, functional or effective) between the nodes.^{78,79} The major advantage of using graph theory is that the interactions can be examined at a whole-brain level rather than in *a priori* defined ROIs, while also being able to look at the specific role of a certain node in the network. This introduces a novel vocabulary of measures which capture the quality of network integration: (i) the capacity of networks to become interconnected and exchange information as well as the identification of nodes that are of

great importance for this information transfer, and (ii) the degree to which network elements form separate clusters and become segregated.⁸⁰ In healthy young adults, motor and visual networks became more segregated over the course of 6 weeks of visuomotor training.⁸¹ More effective performance of a motor task was thus associated with a brain topology, in which the motor network became less entangled. In PD, there is already a reduction in network integration as well as network segregation at baseline, respectively suggesting that less efficient transfer of information as well as exaggerated compensatory communication is apparent.^{82,83} Even though Levodopa tends to normalize this disturbed network topology,⁸⁴ future research needs to investigate whether such an architectural analysis is sensitive to detect motor learning potential.

A third road for unravelling the potential for neuroplasticity is using a multi modal approach, e.g. either using concurrent EEG-fMRI data or combining structural and functional neuroimaging data acquired on the same patients. The advantage of using a multimodal approach is that the cross-information could potentially reveal variations that may only be partially detected using a single modality.⁸⁵ Moreover, when attempting to understand and predict individual responses, data gathered simultaneously from several modalities can increase accuracy.⁸⁶

An example of a multimodal approach is the combination of EEG and fMRI measurements offering a high temporal and spatial resolution respectively. As motor learning is a highly dynamic process, a high spatial and temporal resolution is desirable to gain an in-depth understanding of what is happening in the brain. To the best of our knowledge, this is currently an unexplored topic in relation to both motor learning and PD, though several studies have looked into the benefits of EEG-fMRI to characterize the neural dynamics of cognitive processes.⁸⁷⁻⁹⁰ So far, most studies focused on combining EEG with BOLD activations, though it has been suggested that using EEG-fMRI can also facilitate a

fuller understanding of brain connectivity.⁹¹ Recent work has identified both Dynamic Causal Modeling (DCM) and Graph Theory as ideal candidates for data fusion.^{92,93}

We did not review changes in structural connectivity as a result of motor learning due to a lack of studies in this domain. However, combining both structural and functional connectivity may provide complementary information on the effects of neurorehabilitation. Still, it has been demonstrated that there is no one-to-one relationship between structural and functional connectivity.^{94,95} In healthy adults, Taubert et al were the first to combine structural and functional scans to investigate whether long-term motor training induced changes in functional connectivity coinciding with structural alterations using a multimodal correlation analyses.⁹⁶ They found that functional connectivity changed between the SMA/pre-SMA and parietal areas. This change overlapped with microstructural alterations in the white matter tracts and correlated with performance improvements. A recent study from the same group showed that gray matter changes were found to underlie balance training in PD,⁹⁷ though a combination with connectivity measures was not investigated.

CONCLUSION

In this review, several consistent findings on brain circuitry changes related to motor learning were highlighted in both healthy people and those with PD. The hallmark of consolidated motor learning appeared to imprint on the degree of entanglement within and between motor and cognitive networks. Even so, current brain connectivity studies reflect variable results and are of methodological insufficient quality to reveal how rehabilitation influences the underlying neural networks in PD. This literature overview uncovered a number of methodological developments that are likely to shed more light on these issues in the future, which in turn can lead to optimized as well as better targeted neurorehabilitation.

REFERENCES

- Jankovic J. Parkinson's disease: clinical features and diagnosis. *J Neurol Neurosurg Psychiatry* 2008; **79**: 368–76. doi: <https://doi.org/10.1136/jnnp.2007.131045>
- Cerasa A, Novellino F, Quattrone A. Connectivity changes in Parkinson's disease. *Curr Neurol Neurosci Rep* 2016; **16**: 91. doi: <https://doi.org/10.1007/s11910-016-0687-9>
- Gao L-L, Wu T. The study of brain functional connectivity in Parkinson's disease. *Transl Neurodegener* 2016; **5**: 18. doi: <https://doi.org/10.1186/s40035-016-0066-0>
- Ng B, Varoquaux G, Poline JB, Thirion B, Greicius MD, Poston KL. Distinct alterations in Parkinson's medication-state and disease-state connectivity. *Neuroimage Clin* 2017; **16**: 575–85. doi: <https://doi.org/10.1016/j.nicl.2017.09.004>
- Tahmasian M, Eickhoff SB, Giehl K, Schwartz F, Herz DM, Drzezga A, et al. Resting-state functional reorganization in Parkinson's disease: an activation likelihood estimation meta-analysis. *Cortex* 2017; **92**: 119–38. doi: <https://doi.org/10.1016/j.cortex.2017.03.016>
- Wu T, Wang L, Hallett M, Chen Y, Li K, Chan P. Effective connectivity of brain networks during self-initiated movement in Parkinson's disease. *Neuroimage* 2011; **55**: 204–15. doi: <https://doi.org/10.1016/j.neuroimage.2010.11.074>
- Dirkx MF, den Ouden H, Aarts E, Timmer M, Bloem BR, Toni I, et al. The cerebral network of Parkinson's tremor: an effective connectivity fMRI study. *J Neurosci* 2016; **36**: 5362–72. doi: <https://doi.org/10.1523/JNEUROSCI.3634-15.2016>
- Helmich RC, Dirkx MF. Pathophysiology and management of parkinsonian tremor. *Semin Neurol* 2017; **37**: 127–34. doi: <https://doi.org/10.1055/s-0037-1601558>
- Mathys C, Caspers J, Langner R, Südmeyer M, Grefkes C, Reetz K, et al. Functional connectivity differences of the subthalamic nucleus related to Parkinson's disease. *Hum Brain Mapp* 2016; **37**: 1235–53. doi: <https://doi.org/10.1002/hbm.23099>
- Connolly B, Fox SH. Treatment of cognitive, psychiatric, and affective disorders associated with Parkinson's disease. *Neurotherapeutics* 2014; **11**: 78–91. doi: <https://doi.org/10.1007/s13311-013-0238-x>

11. Moustafa AA, Chakravarthy S, Phillips JR, Gupta A, Keri S, Polner B, et al. Motor symptoms in Parkinson's disease: a unified framework. *Neurosci Biobehav Rev* 2016; **68**: 727–40. doi: <https://doi.org/10.1016/j.neubiorev.2016.07.010>
12. Gao L-L, Zhang J-R, Chan P, Wu T. Levodopa effect on basal ganglia motor circuit in Parkinson's disease. *CNS Neurosci Ther* 2017; **23**: 76–86. doi: <https://doi.org/10.1111/cns.12634>
13. Tahmasian M, Bettray LM, van Eimeren T, Drzezga A, Timmermann L, Eickhoff CR, et al. A systematic review on the applications of resting-state fMRI in Parkinson's disease: does dopamine replacement therapy play a role? *Cortex* 2015; **73**: 80–105. doi: <https://doi.org/10.1016/j.cortex.2015.08.005>
14. Mak MK, Wong-Yu IS, Shen X, Chung CL. Long-term effects of exercise and physical therapy in people with Parkinson disease. *Nat Rev Neurol* 2017; **13**: 689–703. doi: <https://doi.org/10.1038/nrneurol.2017.128>
15. Shen X, Wong-Yu IS, Mak MKY. Effects of exercise on falls, balance, and gait ability in Parkinson's disease: a meta-analysis. *Neurorehabil Neural Repair* 2016; **30**: 512–27. doi: <https://doi.org/10.1177/1545968315613447>
16. Tomlinson CL, Patel S, Meek C, Herd CP, Clarke CE, Stowe R, et al. Physiotherapy intervention in Parkinson's disease: systematic review and meta-analysis. *BMJ* 2012; **345**: e5004: e5004. doi: <https://doi.org/10.1136/bmj.e5004>
17. Cusso ME, Donald KJ, Khoo TK. The Impact of Physical Activity on Non-Motor Symptoms in Parkinson's Disease: A Systematic Review. *Front Med* 2016; **3**: 35: 35. doi: <https://doi.org/10.3389/fmed.2016.00035>
18. Lauzé M, Daneault J-F, Duval C. The Effects of Physical Activity in Parkinson's Disease: A Review. *J Parkinsons Dis* 2016; **6**: 685–98. doi: <https://doi.org/10.3233/JPD-160790>
19. Penhune VB, Steele CJ. Parallel contributions of cerebellar, striatal and M1 mechanisms to motor sequence learning. *Behav Brain Res* 2012; **226**: 579–91. doi: <https://doi.org/10.1016/j.bbr.2011.09.044>
20. Doyon J, Bellec P, Amsel R, Penhune V, Monchi O, Carrier J, et al. Contributions of the basal ganglia and functionally related brain structures to motor learning. *Behav Brain Res* 2009; **199**: 61–75. doi: <https://doi.org/10.1016/j.bbr.2008.11.012>
21. Katak SS, Winstein CJ. Learning–performance distinction and memory processes for motor skills: a focused review and perspective. *Behav Brain Res* 2012; **228**: 219–31. doi: <https://doi.org/10.1016/j.bbr.2011.11.028>
22. Lehéricy S, Benali H, Van de Moortele P-F, Péligrini-Issac M, Waechter T, Ugurbil K, et al. Distinct basal ganglia territories are engaged in early and advanced motor sequence learning. *Proc Natl Acad Sci U S A* 2005; **102**: 12566–71. doi: <https://doi.org/10.1073/pnas.0502762102>
23. Wu T, Hallett M, Chan P. Motor automaticity in Parkinson's disease. *Neurobiol Dis* 2015; **82**: 226–34. doi: <https://doi.org/10.1016/j.nbd.2015.06.014>
24. Dan X, King BR, Doyon J, Chan P. Motor sequence learning and consolidation in unilateral de novo patients with Parkinson's disease. *PLoS One* 2015; **10**: e0134291: e0134291. doi: <https://doi.org/10.1371/journal.pone.0134291>
25. Heremans E, Nackaerts E, Vervoort G, Broeder S, Swinnen SP, Nieuwboer A. Impaired retention of motor learning of writing skills in patients with Parkinson's disease with freezing of gait. *PLoS One* 2016; **11**: e0148933: e0148933. doi: <https://doi.org/10.1371/journal.pone.0148933>
26. Marinelli L, Quartarone A, Hallett M, Frazzitta G, Ghilardi MF. The many facets of motor learning and their relevance for Parkinson's disease. *Clin Neurophysiol* 2017; **128**: 1127–41. doi: <https://doi.org/10.1016/j.clinph.2017.03.042>
27. Nackaerts E, Heremans E, Vervoort G, Smits-Engelsman BCM, Swinnen SP, Vandenbergh W, et al. Relearning of writing skills in Parkinson's disease after intensive amplitude training. *Mov Disord* 2016; **31**: 1209–16. doi: <https://doi.org/10.1002/mds.26565>
28. Nieuwhof F, Helmich RC. Entangled cerebral networks in Parkinson's disease. *Brain* 2017; **140**: 2767–9. doi: <https://doi.org/10.1093/brain/awx267>
29. Duchesne C, Gheysen F, Bore A, Albouy G, Nadeau A, Robillard ME, et al. Influence of aerobic exercise training on the neural correlates of motor learning in Parkinson's disease individuals. *Neuroimage Clin* 2016; **12**: 559–69. doi: <https://doi.org/10.1016/j.nicl.2016.09.011>
30. Hirsch MA, Iyer SS, Sanjak M. Exercise-induced neuroplasticity in human Parkinson's disease: what is the evidence telling us? *Parkinsonism Relat Disord* 2016; **22 Suppl 1**(Suppl 1): S78–S81. doi: <https://doi.org/10.1016/j.parkreldis.2015.09.030>
31. Maitan I, Rosenberg-Katz K, Jacob Y, Giladi N, Hausdorff JM, Mirelman A. Disparate effects of training on brain activation in Parkinson disease. *Neurology* 2017; **89**: 1804–10. doi: <https://doi.org/10.1212/WNL.0000000000004576>
32. Wu T, Chan P, Hallett M. Modifications of the interactions in the motor networks when a movement becomes automatic. *J Physiol* 2008; **586**: 4295–304. doi: <https://doi.org/10.1113/jphysiol.2008.153445>
33. Wu T, Chan P, Hallett M. Effective connectivity of neural networks in automatic movements in Parkinson's disease. *Neuroimage* 2010; **49**: 2581–7. doi: <https://doi.org/10.1016/j.neuroimage.2009.10.051>
34. Wu T, Liu J, Zhang H, Hallett M, Zheng Z, Chan P. Attention to automatic movements in Parkinson's disease: modified automatic mode in the striatum. *Cereb Cortex* 2015; **25**: 3330–42. doi: <https://doi.org/10.1093/cercor/bhu135>
35. Ginis P, Heremans E, Ferrari A, Bekkers EMJ, Canning CG, Nieuwboer A. External input for gait in people with Parkinson's disease with and without freezing of gait: One size does not fit all. *J Neurol* 2017; **264**: 1488–96. doi: <https://doi.org/10.1007/s00415-017-8552-6>
36. Ginis P, Nackaerts E, Nieuwboer A, Heremans E. Cueing for people with Parkinson's disease with freezing of gait: a narrative review of the state-of-the-art and novel perspectives. *Ann Phys Rehabil Med* 2018; **61**: 407–13. doi: <https://doi.org/10.1016/j.rehab.2017.08.002>
37. Thomas C, Baker CI. Teaching an adult brain new tricks: a critical review of evidence for training-dependent structural plasticity in humans. *Neuroimage* 2013; **73**: 225–36. doi: <https://doi.org/10.1016/j.neuroimage.2012.03.069>
38. Solesio-Jofre E, Beets IAM, Woolley DG, Pauwels L, Chalavi S, Mantini D, et al. Age-dependent modulations of resting state connectivity following motor practice. *Front Aging Neurosci* 2018; **10**: 25. doi: <https://doi.org/10.3389/fnagi.2018.00025>
39. Mary A, Wens V, Op de Beeck M, Leproult R, De Tiège X, Peigneux P. Age-related differences in practice-dependent resting-state functional connectivity related to motor sequence learning. *Hum Brain Mapp* 2017; **38**: 923–37. doi: <https://doi.org/10.1002/hbm.23428>
40. King BR, van Ruitenbeek P, Leunissen I, Cuypers K, Heise K-F, Santos Monteiro T, et al. Age-related declines in motor performance are associated with decreased segregation of large-scale resting state brain networks. *Cereb Cortex* 2018; **28**: 4390–402. doi: <https://doi.org/10.1093/cercor/bhx297>
41. Weng TB, Pierce GL, Darling WG, Falk D, Magnotta VA, Voss MW. The Acute Effects of Aerobic Exercise on the Functional Connectivity of Human Brain Networks.

- Brain Plast* 2017; **2**: 171–90. doi: <https://doi.org/10.3233/BPL-160039>
42. Flodin P, Jonasson LS, Riklund K, Nyberg L, Boraxbekk CJ. Does aerobic exercise influence intrinsic brain activity? an aerobic exercise intervention among healthy old adults. *Front Aging Neurosci* 2017; **9**: 267. doi: <https://doi.org/10.3389/fnagi.2017.00267>
 43. McGregor KM, Crosson B, Krishnamurthy LC, Krishnamurthy V, Hortman K, Gopinath K, et al. Effects of a 12-week aerobic spin intervention on resting state networks in previously sedentary older adults. *Front Psychol* 2018; **9**: 2376. doi: <https://doi.org/10.3389/fpsyg.2018.02376>
 44. Duchesne C, Lungu O, Nadeau A, Robillard ME, Boré A, Bobeuf F, et al. Enhancing both motor and cognitive functioning in Parkinson's disease: aerobic exercise as a rehabilitative intervention. *Brain Cogn* 2015; **99**: 68–77. doi: <https://doi.org/10.1016/j.bandc.2015.07.005>
 45. Manuel AL, Nicastro N, Schnider A, Guggisberg AG. Resting-state connectivity after visuo-motor skill learning is inversely associated with offline consolidation in Parkinson's disease and healthy controls. *Cortex* 2018; **106**: 237–47. doi: <https://doi.org/10.1016/j.cortex.2018.06.005>
 46. Shah C, Beall EB, Frankemolle AMM, Penko A, Phillips MD, Lowe MJ, et al. Exercise therapy for Parkinson's disease: Pedaling rate is related to changes in motor connectivity. *Brain Connect* 2016; **6**: 25–36. doi: <https://doi.org/10.1089/brain.2014.0328>
 47. Nackaerts E, Michely J, Heremans E, Swinnen SP, Smits-Engelsman BCM, Vandenberghe W, et al. Training for micrographia alters neural connectivity in Parkinson's disease. *Front Neurosci* 2018; **12**: 3. doi: <https://doi.org/10.3389/fnins.2018.00003>
 48. Li K, Guo L, Nie J, Li G, Liu T. Review of methods for functional brain connectivity detection using fMRI. *Comput Med Imaging Graph* 2009; **33**: 131–9. doi: <https://doi.org/10.1016/j.compmedimag.2008.10.011>
 49. Coynel D, Marrelec G, Perlberg V, Pélégriani-Issac M, Van de Moortele P-F, Ugurbil K, et al. Dynamics of motor-related functional integration during motor sequence learning. *Neuroimage* 2010; **49**: 759–66. doi: <https://doi.org/10.1016/j.neuroimage.2009.08.048>
 50. Price CJ, Friston KJ. Functional imaging studies of neuropsychological patients: applications and limitations. *Neurocase* 2002; **8**: 345–54. doi: <https://doi.org/10.1076/neur.8.4.345.16186>
 51. Herz DM, Siebner HR, Hulme OJ, Florin E, Christensen MS, Timmermann L. Levodopa reinstates connectivity from prefrontal to premotor cortex during externally paced movement in Parkinson's disease. *Neuroimage* 2014; **90**: 15–23. doi: <https://doi.org/10.1016/j.neuroimage.2013.11.023>
 52. Nettersheim FS, Loehrer PA, Weber I, Jung F, Dembek TA, Pelzer EA, et al. Dopamine substitution alters effective connectivity of cortical prefrontal, premotor, and motor regions during complex bimanual finger movements in Parkinson's disease. *Neuroimage* 2018; **23** Apr 2018. doi: <https://doi.org/10.1016/j.neuroimage.2018.04.030>
 53. Wu T, Zhang J, Hallett M, Feng T, Hou Y, Chan P. Neural correlates underlying micrographia in Parkinson's disease. *Brain* 2016; **139**(Pt 1): 144–60. doi: <https://doi.org/10.1093/brain/awv319>
 54. Tuite P. Brain Magnetic Resonance Imaging (MRI) as a Potential Biomarker for Parkinson's Disease (PD). *Brain Sci* 2017; **7**: E68: 68: 16 06 2017. doi: <https://doi.org/10.3390/brainsci7060068>
 55. Corcos DM, Robichaud JA, David FJ, Leurgans SE, Vaillancourt DE, Poon C, et al. A two-year randomized controlled trial of progressive resistance exercise for Parkinson's disease. *Mov Disord* 2013; **28**: 1230–40. doi: <https://doi.org/10.1002/mds.25380>
 56. Heremans E, Nieuwboer A, Spildooren J, Vandebosche J, Deroost N, Soetens E, et al. Cognitive aspects of freezing of gait in Parkinson's disease: a challenge for rehabilitation. *J Neural Transm* 2013; **120**: 543–57. doi: <https://doi.org/10.1007/s00702-012-0964-y>
 57. Intzandt B, Beck EN, Silveira CRA. The effects of exercise on cognition and gait in Parkinson's disease: a scoping review. *Neurosci Biobehav Rev* 2018; **95**: 136–69. doi: <https://doi.org/10.1016/j.neubiorev.2018.09.018>
 58. Reynolds GO, Otto MW, Ellis TD, Cronin-Golomb A. The therapeutic potential of exercise to improve mood, cognition, and sleep in Parkinson's disease. *Mov Disord* 2016; **31**: 23–38. doi: <https://doi.org/10.1002/mds.26484>
 59. Stephan MA, Meier B, Zaugg SW, Kaelin-Lang A. Motor sequence learning performance in Parkinson's disease patients depends on the stage of disease. *Brain Cogn* 2011; **75**: 135–40. doi: <https://doi.org/10.1016/j.bandc.2010.10.015>
 60. Strouwen C, Molenaar EALM, Münks L, Broeder S, Ginis P, Bloem BR, et al. Determinants of Dual-task training effect size in Parkinson disease: Who will benefit most? *J Neurol Phys Ther* 2019; **43**: 3–11. doi: <https://doi.org/10.1097/NPT.0000000000000247>
 61. Wu J, Srinivasan R, Kaur A, Cramer SC. Resting-state cortical connectivity predicts motor skill acquisition. *Neuroimage* 2014; **91**: 84–90. doi: <https://doi.org/10.1016/j.neuroimage.2014.01.026>
 62. Manuel AL, Guggisberg AG, Thézé R, Turri F, Schnider A. Resting-state connectivity predicts visuo-motor skill learning. *Neuroimage* 2018; **176**: 446–53. doi: <https://doi.org/10.1016/j.neuroimage.2018.05.003>
 63. Wu J, Knapp F, Cramer SC, Srinivasan R. Electroencephalographic connectivity measures predict learning of a motor sequencing task. *J Neurophysiol* 2018; **119**: 490–8. doi: <https://doi.org/10.1152/jn.00580.2017>
 64. Mary A, Wens V, Op de Beek M, Leproult R, De Tiège X, Peigneux P. Resting-state functional connectivity is an age-dependent predictor of motor learning abilities. *Cereb Cortex* 2017; **27**: 4923–32. doi: <https://doi.org/10.1093/cercor/bhw286>
 65. Mattar MG, Wymbs NF, Bock AS, Aguirre GK, Grafton ST, Bassett DS. Predicting future learning from baseline network architecture. *Neuroimage* 2018; **172**: 107–17. doi: <https://doi.org/10.1016/j.neuroimage.2018.01.037>
 66. Bogdanov P, Dereli N, Dang X-H, Bassett DS, Wymbs NF, Grafton ST, et al. Learning about learning: mining human brain sub-network biomarkers from fMRI data. *PLoS One* 2017; **12**: e0184344. doi: <https://doi.org/10.1371/journal.pone.0184344>
 67. Akram H, Wu C, Hyam J, Foltyn T, Limousin P, De Vita E, et al. L-dopa responsiveness is associated with distinctive connectivity patterns in advanced Parkinson's disease. *Mov Disord* 2017; **32**: 874–83. doi: <https://doi.org/10.1002/mds.27017>
 68. Herz DM, Haagensen BN, Nielsen SH, Madsen KH, Løkkegaard A, Siebner HR. Resting-state connectivity predicts levodopa-induced dyskinesias in Parkinson's disease. *Mov Disord* 2016; **31**: 521–9. doi: <https://doi.org/10.1002/mds.26540>
 69. Vaillancourt DE, Schonfeld D, Kwak Y, Bohnen NI, Seidler R. Dopamine overdose hypothesis: evidence and clinical implications. *Mov Disord* 2013; **28**: 1920–9. doi: <https://doi.org/10.1002/mds.25687>
 70. Kwak Y, Müller MLTM, Bohnen NI, Dayalu P, Seidler RD. Effect of dopaminergic medications on the time course of explicit motor sequence learning in Parkinson's disease. *J Neurophysiol* 2010; **103**: 942–9. doi: <https://doi.org/10.1152/jn.00197.2009>
 71. Kwak Y, Müller MLTM, Bohnen NI, Dayalu P, Seidler RD. L-dopa changes ventral striatum recruitment during motor sequence learning in Parkinson's disease. *Behav Brain*

- Res 2012; **230**: 116–24. doi: <https://doi.org/10.1016/j.bbr.2012.02.006>
72. King LA, Peterson DS, Mancini M, Carlson-Kuhta P, Fling BW, Smulders K, et al. Do cognitive measures and brain circuitry predict outcomes of exercise in Parkinson disease: a randomized clinical trial. *BMC Neurol* 2015; **15**: 218. doi: <https://doi.org/10.1186/s12883-015-0474-2>
 73. Bassett DS, Sporns O. Network neuroscience. *Nat Neurosci* 2017; **20**: 353–64. doi: <https://doi.org/10.1038/nn.4502>
 74. Hohenfeld C, Werner CJ, Reetz K. Resting-state connectivity in neurodegenerative disorders: is there potential for an imaging biomarker? *Neuroimage Clin* 2018; **18**: 849–70. doi: <https://doi.org/10.1016/j.nicl.2018.03.013>
 75. Tagliazucchi E, Laufs H. Decoding wakefulness levels from typical fMRI resting-state data reveals reliable drifts between wakefulness and sleep. *Neuron* 2014; **82**: 695–708. doi: <https://doi.org/10.1016/j.neuron.2014.03.020>
 76. Shine JM, Poldrack RA. Principles of dynamic network reconfiguration across diverse brain states. *Neuroimage* 2018; **180**(Pt B): 396–405. doi: <https://doi.org/10.1016/j.neuroimage.2017.08.010>
 77. Sporns O. Cerebral cartography and connectomics. *Philos Trans R Soc Lond B Biol Sci* 2015; **370**: 2014017319 May 2015. doi: <https://doi.org/10.1098/rstb.2014.0173>
 78. Bullmore E, Sporns O. Complex brain networks: graph theoretical analysis of structural and Functional Systems. *Nat Rev Neurosci* 2009; **10**: 186–98. doi: <https://doi.org/10.1038/nrn2575>
 79. Rubinov M, Sporns O. Complex network measures of brain connectivity: uses and interpretations. *Neuroimage* 2010; **52**: 1059–69. doi: <https://doi.org/10.1016/j.neuroimage.2009.10.003>
 80. Sporns O. Structure and function of complex brain networks. *Dialogues Clin Neurosci* 2013; **15**: 247–62.
 81. Bassett DS, Yang M, Wymbs NF, Grafton ST. Learning-induced autonomy of sensorimotor systems. *Nat Neurosci* 2015; **18**: 744–51. doi: <https://doi.org/10.1038/nn.3993>
 82. Kim J, Criaud M, Cho SS, Díez-Cirarda M, Mihaescu A, Coakeley S, et al. Abnormal intrinsic brain functional network dynamics in Parkinson's disease. *Brain* 2017; **140**: 2955–67. doi: <https://doi.org/10.1093/brain/awx233>
 83. Suo X, Lei D, Li N, Cheng L, Chen F, Wang M, et al. Functional brain connectome and its relation to Hoehn and Yahr stage in Parkinson disease. *Radiology* 2017; **285**: 904–13. doi: <https://doi.org/10.1148/radiol.2017162929>
 84. Berman BD, Smucny J, Wylie KP, Shelton E, Kronberg E, Leehey M, et al. Levodopa modulates small-world architecture of functional brain networks in Parkinson's disease. *Mov Disord* 2016; **31**: 1676–84. doi: <https://doi.org/10.1002/mds.26713>
 85. Sui J, Huster R, Yu Q, Segall JM, Calhoun VD. Function-structure associations of the brain: evidence from multimodal connectivity and covariance studies. *Neuroimage* 2014; **102 Pt 1**(Pt 1): 11–23. doi: <https://doi.org/10.1016/j.neuroimage.2013.09.044>
 86. Bowman FD, Drake DF, Huddleston DE. Multimodal imaging signatures of Parkinson's disease. *Front Neurosci* 2016; **10**: 131. doi: <https://doi.org/10.3389/fnins.2016.00131>
 87. Andreou C, Frielinghaus H, Rauh J, Mußmann M, Vauth S, Braun P, et al. Theta and high-beta networks for feedback processing: a simultaneous EEG-fMRI study in healthy male subjects. *Transl Psychiatry* 2017; **7**: e1016: e1016. doi: <https://doi.org/10.1038/tp.2016.287>
 88. Fouragnan E, Retzler C, Mullinger K, Philiastrides MG. Two spatiotemporally distinct value systems shape reward-based learning in the human brain. *Nat Commun* 2015; **6**: 8107. doi: <https://doi.org/10.1038/ncomms9107>
 89. Hauser TU, Hunt LT, Iannaccone R, Walitza S, Brandeis D, Brem S, et al. Temporally dissociable contributions of human medial prefrontal subregions to reward-guided learning. *J Neurosci* 2015; **35**: 11209–20. doi: <https://doi.org/10.1523/JNEUROSCI.0560-15.2015>
 90. Ostwald D, Porcaro C, Mayhew SD, Bagshaw AP. EEG-fMRI based information theoretic characterization of the human perceptual decision system. *PLoS One* 2012; **7**: e33896: e33896. doi: <https://doi.org/10.1371/journal.pone.0033896>
 91. He B, Liu Z. Multimodal functional neuroimaging: integrating functional MRI and EEG/MEG. *IEEE Rev Biomed Eng* 2008; **1**: 23–40. doi: <https://doi.org/10.1109/RBME.2008.2008233>
 92. Nguyen VT, Breakspear M, Cunnington R. Fusing concurrent EEG-fMRI with dynamic causal modeling: application to effective connectivity during face perception. *Neuroimage* 2014; **102 Pt 1**(Pt 1): 60–70. doi: <https://doi.org/10.1016/j.neuroimage.2013.06.083>
 93. Yu Q, Wu L, Bridwell DA, Erhardt EB, Du Y, He H, et al. Building an EEG-fMRI multimodal brain graph: a concurrent EEG-fMRI study. *Front Hum Neurosci* 2016; **10**: 476. doi: <https://doi.org/10.3389/fnhum.2016.00476>
 94. Honey CJ, Sporns O, Cammoun L, Gigandet X, Thiran JP, Meuli R, et al. Predicting human resting-state functional connectivity from structural connectivity. *Proc Natl Acad Sci U S A* 2009; **106**: 2035–40. doi: <https://doi.org/10.1073/pnas.0811168106>
 95. Stam CJ, van Straaten ECW, Van Dellen E, Tewarie P, Gong G, Hillebrand A, et al. The relation between structural and functional connectivity patterns in complex brain networks. *Int J Psychophysiol* 2016; **103**: 149–60. doi: <https://doi.org/10.1016/j.ijpsycho.2015.02.011>
 96. Taubert M, Lohmann G, Margulies DS, Villringer A, Ragert P. Long-term effects of motor training on resting-state networks and underlying brain structure. *Neuroimage* 2011; **57**: 1492–8. doi: <https://doi.org/10.1016/j.neuroimage.2011.05.078>
 97. Sehm B, Taubert M, Conde V, Weise D, Classen J, Dukart J, et al. Structural brain plasticity in Parkinson's disease induced by balance training. *Neurobiol Aging* 2014; **35**: 232–9. doi: <https://doi.org/10.1016/j.neurobiolaging.2013.06.021>