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# The integration of clinical data in the assessment of Multiple Sclerosis - a review

Sofia Ostellino<sup>a</sup>, Alfredo Benso<sup>a</sup>, Gianfranco Politano<sup>a,\*</sup>

<sup>a</sup>*Department of Control and Computer Engineering, Politecnico di Torino, Italy*

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## Abstract

**Background and Objectives:** Multiple Sclerosis (MS) is a neurological disease associated with various and heterogeneous clinical characteristics. Given its complex nature and its unpredictable evolution over time, there isn't an established and exhaustive clinical protocol (or tool) for its diagnosis nor for monitoring its progression. Instead, different clinical exams and physical/psychological evaluations need to be taken into account. The Expanded Disability Status Scale (EDSS) is the most used clinical scale, but it suffers from several limitations. Developing computational solutions for the identification of bio-markers of disease progression that overcome the downsides of currently used scales is crucial and is gaining interest in current literature and research. **Methods:** This Review focuses on the importance of approaching MS diagnosis and monitoring by investigating correlations between cognitive impairment and clinical data that refer to different MS domains. We review papers that integrate heterogeneous data and analyse them with statistical methods to understand their applicability into more advanced computational tools. Particular attention is paid to the impact that computational approaches can have on personalized medicine. **Results:** Personalized medicine for neuro-degenerative diseases is an unmet clinical need which can be addressed using computational approaches able to efficiently integrate heterogeneous clinical data extracted from both pri-

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\*Corresponding author

*Email addresses:* [sofia.ostellino@polito.it](mailto:sofia.ostellino@polito.it) (Sofia Ostellino), [alfredo.benso@polito.it](mailto:alfredo.benso@polito.it) (Alfredo Benso), [gianfranco.politano@polito.it](mailto:gianfranco.politano@polito.it) (Gianfranco Politano)

vate and publicly available electronic health databases. **Conclusions:** Reliable and explainable Artificial Intelligence are computational approaches required to understand the complex and demonstrated interactions between MS manifestations as well as to provide reliable predictions on the disease evolution, representing a promising research field.

### Highlights

- Multiple Sclerosis (MS) progression needs to be monitored through heterogeneous clinical measures.
- Cognitive assessment via neuropsychological tests (NP) is fundamental and informative in MS monitoring.
- Computerized NPs allow good quality and efficient cognitive examinations.
- Computational integration of data related to different neurodegenerative disease domains is a promising research field.
- Artificial Intelligence is, at the moment, the most promising computational approach to extract new knowledge from large sets of available clinical data.

*Keywords:* Multiple Sclerosis, Clinical data, Computational integration, Neuropsychological tests, Cognitive assessment, Personalized medicine, Bio-markers

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## 1. Introduction

Multiple sclerosis (MS) is a chronic disease characterized by intra-patient and inter-patient variability in terms of disease course, progression, and efficacy of treatments. MS, like other neurodegenerative conditions, is a wide spectrum disease which multisymptomatic characteristics require a comprehensive health evaluation at both diagnosis and follow-up. Disease monitoring is crucial and

challenging as MS involves multiple physiological domains: there isn't a single and widely accepted bio-marker informative enough to be used for planning a personalized treatment. For this reason, a lot of research is currently focused  
10 on the identification of bio-markers [1] for personalized predictions.

### 1.1. Disease characteristics

MS is a complex chronic autoimmune disease that affects the central nervous system (CNS): myelinated axons are attacked by the immune system, a process leading to a wide spectrum of symptoms depending on the localization of the  
15 resulting lesion. Main symptoms, as summarized in Figure 1, include optic neuritis, partial myelopathy, dizziness, motor dysfunctions, fatigue, loss of balance, paraesthesia, depression, and cognitive impairment [2].

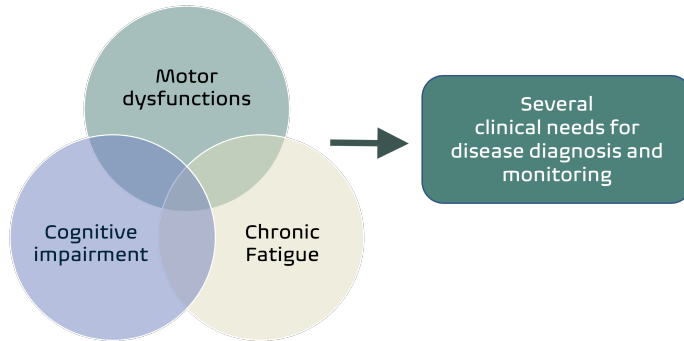


Figure 1: MS diversified symptomatology.

MS is typically diagnosed in young adults (twice as many women are involved as men) between 20 and 40 years of age and is usually characterized by an  
20 accumulation of disability in time, having a massive impact on everyday life. Three MS clinical phenotypes are well-defined according to the time interval between relapses, the recovery capacity, and the accumulation of disability [3]: *Relapsing-relmitting MS (RRMS)* and *Primary-progressive MS (PPMS)* are the two main clinical sub-types that characterize the onset in the 85% and 10-15%  
25 of the cases, respectively; over 2/3 of RRMS cases will convert to *Secondary-progressive MS (SPMS)* within 10/15 years,

Both genetic and environmental aspects have a significant role in MS onset and, although a cure is not known yet, several disease modifying therapies (DMTs) are available. DMTs aim at delaying the progression of the disease and the consequent accumulation of disability, primarily avoiding the formation of new lesions [4]. Nowadays[5], 2.8 million people are living with MS around the globe (1 in 3,000 people). In Italy, 127,317 (1 every 500 people) people are living with MS, and 3.400 new people are diagnosed with MS every year (approximately 283 diagnoses every month). Since it is a chronic disease, MS represents a lifetime cost for the patient, caregivers, and the whole healthcare system. MS costs can be divided in direct (i.e. medical visits, MRI) and indirect costs (i.e. lack of productivity at work), which are more difficult to estimate properly, but are significantly higher than direct costs by a factor of three [6]. In Italy, MS direct costs for each patient range between 20,000 and 39,000 euros per year [7]. Since DMTs (Disease Modifying Therapies) represent the largest direct medical cost for both patients and the health-care system, it is crucial to choose the most suitable treatment for each patient, as well as to change it when it loses efficacy, minimizing the risk of administering the wrong combination of therapies, and losing precious time and economical resources. In current medical practice, therapies are often selected and modified by trial-and-error[8, 9].

### *1.2. Challenges of personalized medicine for MS*

MS is commonly differentially diagnosed following a suspect clinical manifestation, a condition identified as a clinically isolated syndrome (CIS). McDonald criteria are used and accepted by clinicians to confirm and guide the differential diagnosis of MS, and to minimize the risk of misdiagnosis, as the spectrum of MS symptoms is wide and may overlap with other diseases [10]. Since there is not a single diagnostic tool or a single symptom suggestive of MS, its diagnosis requires combining different clinical evaluations that include [2]:

- MRI data (lesion load and brain atrophy that assess lesion dissemination in time and space, and neurodegeneration),

- visual, motor, and sensory evoked potentials,
- cerebrospinal fluid (CSF) examination,
- general neurological examination.

Although, the Extended Disability Status Scale (EDSS) and the Multiple  
60 Sclerosis Functional Composite (MSFC) are two accepted clinical measures  
(COMs) of the disease severity and progression[11], they cannot be considered  
complete, reliable, and exhaustive tools. EDSS is more used than MSFC but  
has some limitations, as EDSS scores can vary a lot due to the complex scor-  
ing rules and the subjectivity of the examiner. EDSS lacks linearity between  
65 score difference and clinical severity and it relies heavily on the evaluation of  
motor function and the ability to walk. Neither EDSS nor MSFC use MRIs  
evaluation in their scores. The main features on which COMs rely are their  
validity, their reliability, and their sensitivity to change. In recent years, EDSS  
limitations have pushed for the development of new, more comprehensive, and  
70 reliable COMs. Unfortunately, the inclusion of the evaluation of cognitive func-  
tions, fatigue, depression, and many other relevant features, is difficult because  
it is not clear how these hidden symptoms interact, and how to reliably evaluate  
and consistently quantify them [12].

Among these above mentioned hidden symptoms, the prevalence of cogni-  
75 tive impairment (CI) in MS is very high, ranging between 40% and 65%[13],  
and it is present in all MS subtypes (in terms of performances and affected  
domains)[14]. The cognitive domains impaired in MS are information process-  
ing speed, learning, and working memory, visual-spatial processing, executive  
functions and verbal fluency. Cognitive functions can be evaluated via different  
80 neuropsychological (NP) test batteries that estimate the degree of impairment  
through a variety of tasks that target different domains [14, 15]. Despite the  
profound effect of CI on the quality of life, and its presence since the very  
beginning of the disease, it is often neglected and not routinely assessed [16].

It is therefore clear that personalized medicine for neurodegenerative dis-  
85 eases like MS is an unmet clinical need, and that the currently used clinical and

imaging bio-markers are not able to follow disease progression at an individual level. In this context is thus crucial to adopt and implement tools that rely on multidimensional and composite prognostic bio-markers, taking into consideration the widest possible set of symptoms [16, 14].

## 90 2. Materials and Methods

This Review focuses on how, given the presence of correlations between different clinical data, computational methods belonging to the Machine Learning field can mitigate the limitations of current evaluation scales. To understand the complex interplay between MS manifestations and to provide reliable  
95 predictions on the disease evolution, requires both a systematic collection of heterogeneous clinical assessments, and reliable and explainable computational approach. In this context, Artificial Intelligence is becoming more and more reliable in identifying (bio)markers by integrating and analyzing large sets of data, and in discovering hidden knowledge and patterns[17]. However, such  
100 methods need to be trained on a huge amount of data, in order to be robust. Several databases that collect MS data do exist, for example the MSBase<sup>1</sup> dataset, or the Italian Multiple Sclerosis Registry<sup>2</sup>. Since the integration of data from different domains is a key step in analyzing SM progression, we analyze the most significant papers where NP test data for CI assessment is coupled  
105 with the investigation of different clinical features and measures, such as the analysis of brain magnetic resonance images (MRI), motor and gait functions, EDSS, and others. MS impact on the brain is usually investigated through MRI imaging. Automatic image analysis is an open field in literature, and while some of the presented papers adopted automatic measures, some others relied  
110 on manual annotation or visual estimation of image characteristics. The focus on CI is justified by its subtle and informative nature that can be assessed with non-invasive methods. Computerized NP tests enable a reliable and "normal-

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<sup>1</sup><https://www.msbase.org/>

<sup>2</sup><https://registroitalianosm.it/en/index.php>

ized” data collection, which is the first step towards the quantification of the test performance, and the standardization of its administration.[1]. We explore how such contributions could pave the way to personalized medicine for the identification of bio-markers at an individual level, demonstrating the presence of correlation between different clinical measures which can in turn represent a knowledge base for the development of computational methods. We included both papers that adopted traditional paper-and-pencil or oral NP tests, as well as those which used computerized NP tests.

### 2.1. Selection criteria

We looked at papers published between 2000 and 2021 that evaluate the cognitive impairment of at least one cognitive domain via a NP test (administered either via a traditional paper-and-pencil approach or a computerized approach), and that look for correlations between cognitive measures and other clinical evidences. We selected 36 papers that explore the relationship between CI and MR images characteristics, and 32 papers that explore the CI in connection with motor functioning, fatigue and depression, as shown in Figure 2.



Figure 2: Works selection.

Since our focus is the integration of multi-domain data, we filtered out those works that do not investigate the relationships between cognitive impairment and at least two other disease domains. 24 papers were finally taken into consideration, 16 of which implement a computerized NP test by re-adapting a single traditional standardized test (oral or paper-and-pencil), or a complete NP test battery. The analysis carried out in the papers relies mostly on standard (and sometimes automated) statistical methods; the central point of our review is not



to discuss the methods, but instead to focus on the type of data they process and on their performances in order to understand their applicability into more advanced computational methods.

Although different single tests or test batteries are used, each paper eval-  
140 uates more than one cognitive domain, and information processing speed is  
always taken into consideration. Self-administration plays a key role: some of  
the computerized tests were implemented to be smartphone-applications, with  
the aim of facilitating self-administration, while others are intended to be self-  
administered in clinics without any need for trained personnel. Cognitive assess-  
145 ment has different duration, spanning from a few minutes to hours, and different  
disease aspects are examined. Computerized tests permit data manipulation,  
facilitating multi-centre studies, standardization, and test administration during  
a single visit, thus saving precious time and resources [15]. Moreover, comput-  
erized applications make it easier to accurately measure reaction times that are  
150 crucial for the evaluation of the impairment of information processing speed  
that is the majorly involved cognitive domain; moreover, they can be integrated  
in self-monitoring smartphone applications that the patients can periodically  
use outside the clinic.

A rapid insight on the papers is given in Table 1 (computerized NP tests),  
155 and Table 2 (not computerized NP tests). For each paper we report the type  
of NP testing that was carried out, the duration of such testing (if given, in  
minutes), the type of MRI analysis and MRI metrics (if present), and other  
clinical data such as EDSS or motor function scales taken into consideration for  
patient assessment.

Table 1: Papers where NP tests are computerized

<b>Author</b>	<i>NPtest</i>	<i>Duration (min)</i>	<i>Score</i>	<i>MRI metrics</i>	<i>MRI analysis</i>	<i>Other Data</i>
Golan et. al [18]	CAB	60	Global cognitive score (GCS)	GM volume, WM volume	Automatic - icobrainms	EDSS, Patient determined disease steps (PDSS)
Razavi et. al [19]	ICA	5	ICS score	-	-	Serum neurofilaments NFL
Pham et. al [20]	MS Suite Test	15	Tests scores	Brain parenchymal fraction, T2 lesion load	Automatic	EDSS
Cohen et. al [21]	MSST	A few	MSST score	GM and WM volume, lesion load	SIENAX segmentation	-
Dongen et. al [22]	Multiple Screener	15	Tests scores	-	-	EDSS, disease severity, depression
Cotter et. al [23]	CANTAB	15	Test scores	-	-	Depression (GDS scale), EDSS, disease duration
Rudick et. al [24]	MSPT	30	Test scores	-	-	EDSS, disease duration, patient report
Rao et. al [25]	PST, 9PHT	A few	Test scores	T2 lesion load	Manual	EDSS
Edgar et. al [26]	CDR	20	Test scores	-	-	9PHT, EDSS, MSFC
Sonneville et. al [27]	Amsterdam NP test	70	Test scores	-	-	EDSS, disease duration
Lapshin et. al [28]	SDMT, PASAT	20	Test scores	-	-	-

Pellicano et. al [29]	ANAM	30	Test scores	-	-	EDSS
Achiron et. al [30]	MCCB	50	GCS	T2 lesions volume, cortical thickness	Automatic	-
Boukalova et. al [31]	SDMT, PASAT	15	Tests scores	-	-	Level test
Arnett et. al [32]	SDMT, PASAT	15	Tests scores	-	-	Depression, coping
Papathan. et. al [33]	CNS-VS	30	Test scores	-	-	EDSS, depression
Macaron et. al [34]	PST	-	Test scores	Semi-automatic	Cord atrophy and deep GM volumes	Depression, multiple PROMs, employment
Baldassarri et. al [35]	NPTs	-	Test scores	Fully-automatic	T2LV, WBF, TV, CA	Multiple PROMs

Table 2: Papers where NP tests are not computerized

<b>Author</b>	<i>NPtest</i>	<i>Duration (min)</i>	<i>Score</i>	<i>MRI metrics</i>	<i>MRI analysis</i>	<i>Other Data</i>
Kuhle et. al [36]	BVMTR, CVLTII, and JLO	90	Test scores	-	-	NfL, EDSS, 9PHT, T25FWT
Kiiski et. al [37]	Adapted MACFIMS	35	Test scores	-	-	Evoked potentials ERPs
Patti et. al [38]	SDMT, PASAT, MCST and SRWL	90	Test scores	GM, WM volume	Automatic	EDSS
D’Orio et. al [39]	CVLT-II, BCMT-R, COWAT, WCST, PASAT	-	Test scores	-	-	Self-reported fall frequency, T25FWT

Lund et. al [40]	32 tests battery	-	Global score	T2 lesion load and volumes, normal appearing brain tissue	Semi-automatic thresholding	EDSS, MSIS
Sandi et. al [41]	BICAMS	15	BICAMS score	-	-	Fatigue, EDSS
Batista et. al [42]	-	Test score	Thalamus and neocortical atrophy	Semi-automatic	-	EDSS

### 160 3. Results

From the analysis of selected papers and the results they present, we infer some considerations about the existence of correlation between clinical data like MRI imaging and the types of NP tests mostly used for CI.

Golan et al.[18] explored the associations between brain volumes and cognitive scores derived from the Cognitive Assessment Battery (CAB). They focused on the most common MS phenotype, relapsing-remitting MS supporting the power of multi-domain assessment. They show a strong correlations between the global cognitive performance and brain volumes, both in grey matter and white matter, and highlight the possibility of investigating brain pathology through cognitive assessment, as thalamic and lateral ventricles volumes correlated with cognitive performance better than lesions and cortical volumes.

While the CAB battery requires 60 minutes to be completed, the test developed by Pham et al.[20] emulates the Symbol Digit Modalities Test (SDMT) [43] with a 15-minute smartphone-based application that is part of the MS Suite Test, a self-administered comprehensive battery. Test score positively correlated with brain parenchymal fraction and T2 lesion load. The cognitive domain targeted by such test is the information processing speed: traditional orally administered paper-and-pencil SDMT evaluates the performance by counting the

number of correct responses, losing information about reaction times and in-  
sights on test execution. These information are instead not lost and easy to  
180 compute with a computerized approach.

The Processing Speed Test (PST), an iPad version for the SDMT, was de-  
veloped by Rao et al. [25]: PST correlated with T2 white matter lesion load  
more strongly than SDMT, making the PST a more valid indicator of brain  
185 damage involvement in MS symptomatology. CI can manifest early and silently  
in disease course, when its signs are not detectable with traditional paper tests,  
and it would be useful to rely on tools that permit the identification of those  
patients for which the risk of conversion from the radiologically isolated syn-  
drome (RIS) to the clinically defined MS (CDMS) is high and who benefit of a  
190 therapeutic intervention strategy before conversion, as the 51% of RIS patients  
convert to MS in 5 years from onset.

The extensive work of Macaron et al. [34] point out the value of the PST test:  
they demonstrate that the PST score is less susceptible to mood effects, and  
that it is associated with MRI metrics such as the measures of diffuse and focal  
195 white and gray matter injury. They suggest that the PST can be a valid marker  
of neurodegeneration. Baldassarri et al. [35] evaluated the associations between  
neuroperformance tests (NPTs), patient reported outcome measures (PROMs)  
and MRI metric, on one of the largest patient cohorts: among the NPTs they  
included the PST, the contrast sensitivity test (CST), the manual dexterity  
200 (MDT), and the walking speed test (WST). A fully-automated MRI analysis  
was performed, calculating the T2-lesion (T2LV) and thalamic (TV) volumes,  
the whole brain fraction (WBF), and the cervical spinal cord cross-sectional area  
(CA): this study is an example of a comprehensive and multi-domain assessment  
that enables to detect disease worsening.

205 The MS Screen Test (MSST) smartphone-based application battery was ad-  
ministered to a population of RIS patients by Cohen et al.[21], who managed to  
distinguish between healthy control and RIS patients, identifying correlations  
between MSST performances and gray/white matter volumes, and lesion load.

The involvement of cortical pathology and the interplays of gray and white

210 matter damage was also reported by Pellicano et al.[29] and Achiron et al.[30].  
They did not rely on self-assessment tools, but instead implemented time de-  
manding computerized batteries; they demonstrated the relevance of the re-  
lationship between CI and the damage of normal appearing grey matter and  
white matter volume loss in specific brain regions, that is not detectable with  
215 traditional MRI analysis.

Pellicano et al.[29] explored the role of normal-appearing white matter, cor-  
tical and normal-appearing gray matter volumes. They found correlations be-  
tween test performances and brain volumes acquired with high-field MRI.

Achiron et al. [30] applied high-resolution imaging and observed that cortical  
220 thickness was present in specific brain regions and correlated with test scores.  
Although they did not consider several MS phenotypes, their results put in  
evidence that cortical pathology is related to cognitive impairment and that it  
involves specific brain areas.

Subclinical MS manifestations are lost with usual clinical assessment meth-  
225 ods and need to be monitored with constancy. As already said, self-assessment  
permits the adaptation of tools for home testing and, if used in clinics, does  
not require the presence of a clinician, saving time and economical resources.  
This concept was exemplified by Dongen et al.[22], that adapted the Brief Inter-  
national Cognitive Assessment for MS (BICAMS) battery in the computerized  
230 Multiple Screener Battery, demonstrating its reliability, stressing the necessity  
of providing clinicians with digital tools for a rapid screening of MS patients, in  
order to collect baseline data and follow-up data.

As mentioned before, one of the needs in the monitoring of people with MS  
is the identification of the conversion between phenotypes: Lapshin et al.[28]  
235 did not specifically looked for correlations between clinical data but did demon-  
strate that via computerized tests it is possible to find differences between MS  
phenotypes, including the clinically isolated syndrome. The identification of  
disease phenotypes is crucial and challenging; Papathanasiou et al.[33] focused  
on RRMS and SPMS using the CNS-VS computerized batteries, pointing out  
240 the inadequacy of traditional tests, their dependence upon neuropsychologists,

and the amount of time required for carrying out the test and interpreting the results. However, they did not find specific cognitive patterns characteristic of each sub-type; this is suggestive of a highly variable neuropsychological conditions within the same disease type that is worth further exploring, relying on the  
245 assumption that a single clinical evidence cannot be sensitive to MS variability, neither NP tests, nor MRI measures.

Other MS characteristics need to be taken into consideration to complete the picture, such as disease course, its severity, duration, the degree of disability, and other factors. The Integrated Cognitive Assessment (ICA) battery developed by Razavi et al.[19] is feasible for a high-frequency administration, and  
250 strongly correlated with the level of serum neurofilament (NFL), a promising fluid biomarker that reflects neuronal damage for brain disorders. The correlation with the ICA scores is relevant as fluid biomarkers evaluation have higher costs and invasivity, lower accessibility and cannot be remotely tested.

The EDSS is the most used clinical outcome measure and brings with it several limitations: Rudick et al.[24] developed the MSPT to efficiently examine cognition, manual dexterity, visual function, balance, and walking speed via an iPad-based application, adapting the traditional 9PHT and SDMT in a new computerized version. Their findings correlated with EDSS estimated by clinicians without being prone to the reader and allowing repeatable results. The  
260 MSPT is therefore proposed as a valid alternative to EDSS.

Cotter et al. [23], used the Cambridge Neuropsychological Test Automated Battery (CANTAB) and took into consideration both the EDSS and depression, that was evaluated via a touchscreen version of the Geriatric Depression Scale (GDS).  
265

Subtle but typical symptoms of MS are depression and fatigue, both difficult to objectively quantify. Arnett et al.[32] showed how depression and coping strategies are related to traditional SDMT and Paced Auditory Serial Addition Test (PASAT) scores, presenting the complex interactions between cognition and psychological conditions, where coping mechanisms vary between subjects,  
270 influencing depression and quality of life.

Studies included in this review evaluate fatigue via self-assessment or questionnaires, but it can also be estimated with gait-analysis, as it has several manifestations (Daly et al.[44]), even if it has a high variability, and it is prone  
275 to subjective perception.

The papers presented so far implement computerized tests or batteries for smartphone applications, which take a few minutes to complete, or more extended ones that are thought to be used in clinical setup. Advantages of computerized batteries are evident when comparing them to applications that follow  
280 the traditional approach of paper-and-pencil tests or oral tests. The Montreal Cognitive Assessment (MoCA) test, for instance, was orally administered by Abou et al.[45]. They found a correlation between MoCA paper performances, MRI measures, and physical disability, considering differences in sustained attention between disease phenotypes. Unfortunately, the oral administration of  
285 the test is prone to errors and have all the previous listed drawbacks; it is nevertheless relevant to notice, once again, that disease phenotypes are distinguishable using cognitive assessment.

Paper-and-pencil batteries are, in general, time consuming: the batteries proposed by Patti et al.[38] and Kule et al.[36] are 90 minutes long. Interestingly, Kule et al.[36] attempted to correlate brain volume, lesion load measures,  
290 EDSS, Nine-Hole Peg Test (9PHT), and Timed 25 Foot Walk (25FW) with serum NFL. They did not find significant correlation since NFL levels depend on immunomodulatory treatments that are not taken into consideration in this paper. This highlights the huge number of interplays that occur in MS.

295 Event related potentials (motor, visual or auditory) (ERPs) are another clinical exam often used in clinics to assess disease status and that reflect MS manifestations: Kiiski et al.[37] found that ERPs during a visual odd ball task could predict information processing speed deterioration, correlating ERPs findings with cognitive scores derived from an adaptation of the traditional Minimal  
300 Assessment of Cognitive Function in MS (MACFIMS) battery; given their results, they propose the ERPs as a valid alternative to long and not sensitive batteries to obtain objective and reproducible results.



#### 4. Discussion

Through the analysis performed in this Review, it is possible to conclude  
305 that strong correlations between clinical data do exist. Moreover, the evi-  
dence of correlations between MRI metrics and several CI symptoms, strongly  
suggests that computerized NP assessment should be always paired with tra-  
ditional imaging analysis, being informative and reliable against conventional  
MRI drawbacks, such as its difficulties in detecting cortical lesions.

310 Furthermore, fluid bio-markers are also object of discussion in several papers,  
and the evidence of their correlations with cognitive functions highlights the  
necessity of investigating how expensive or invasive physiological exams and  
NP tests are, related to each other. To understand that, means to understand  
how and when such examination can be used in combination, or when cognitive  
315 assessment can partially substitute time consuming exams that are not always  
administered to large patient cohorts.

The comparison between works that use computerized adaptation of neuro-  
psychological tests and those that perform traditional NP tests, allowed us to  
summarise the advantages of computerized NP assessment:

- 320 • they are not subject to reader's errors when reporting scores,
- they are scalable, accessible,
- they permit a frequent administration and a continuous monitoring of  
MS patients, collecting reliable data while reducing the risk of missing  
important and subtle changes in the clinical status (generally, MS patients  
325 undergo a neurological visit per year).
- they do not necessarily depend on the presence of a clinician, being often  
categorized as a self-assessment tools,
- they are not invasive,
- they permit the measure of precise reaction times during the test,

- 330 • fast NP assessment can be used for detecting those patients who need a full cognitive examination, while allowing a precise and complete screening of every patient,
- they can be integrated with external tools for gait-assessment, ERPs, or eye-tracking technologies, allowing to collect multiple clinical data syn-  
335 chronously, in the exact same conditions.

The evidence of correlations between such clinical metrics and NP tests support the idea of providing neurologists with efficient and clinically meaningful tools for monitoring patients over time, easily including baseline evaluations and progression, and having the possibility of practically manipulating data and  
340 comparing it with standardised data-sets.

Different clinical exams can be computerized: several software applications have been developed for image analysis, fatigue assessment, gait-analysis, and, as we have highlighted in this review, the same thing can be done with cognition. The use of scales or tools that are more precise and valid, is a promising direction  
345 along with the practical adoption of such tools in the everyday clinical practice: the majority of papers selected for this review that followed this approach were published between 2019 and 2020, being a clear sign of the attention that these topics are gaining.

Finally, given the limitations of clinical scales such as EDSS, Artificial Intel-  
350 ligence (AI) approaches, as machine learning or deep learning algorithms, are promising tools to attempt identifying new bio-markers of disease status and progression. AI methods allow the manipulation of big data, extracting useful information that can deepen the knowledge in disease mechanisms, and resolve the unsatisfied need of digital bio-markers [46]. AI is also extremely useful in  
355 highlighting subtle but important differences between subjects, and is therefore a promising approach towards personalized medicine by consolidating the therapeutic choices for every single patient, defining a risk profile, providing supplementary information, and minimizing therapeutic costs.

## 5. Conclusions

360 Personalized medicine for neuro-degenerative diseases like Multiple Sclerosis  
is a still unmet clinical need which can be addressed via efficient data integration  
and extraction from private or publicly available electronic health databases.  
The implementation of computerized cognitive assessment in the routine clinical  
practice is a promising direction that can have practical and positive effects  
365 on MS monitoring, enabling an easy collection and manipulation of clinical data.  
It also allows frequent self-monitoring, which minimizes the risk of losing infor-  
mative but rare disease manifestations, and allows the acquisition of measures  
that can not be detected during traditional examinations, such as reactions to  
stimuli. This field needs further exploration, but its relevance is clear.

370 The complexity of neurological diseases can be tackled with Artificial In-  
telligence approaches. Such methods, to be reliable and explainable, require a  
huge amount of data for training and testing: computerized approaches allow  
the incorporation of clinical data with public available data-set, and this can  
certainly help in the definition of a prognostic bio-marker capable of adequately  
375 integrate information about disease domains.

This Review presented MS as a heterogeneous disease on which it is nec-  
essary to deepen the knowledge taking advantage of the amount of data that  
can be acquired following a computerized approach. It is possible to integrate  
measurements that correspond to different disease domains and the combina-  
380 tion of such evidences can compensate the downsides that, nowadays, hinder an  
efficient implementation of MS patients monitoring, such as costs in terms of  
time and resources.

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