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Quantitative Neuro-Assessment: MRI vs. Electrophysiology in CNS Disease Biomarker Science

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Abstract

Personalized neurological care in hospital settings leverages artificial intelligence (AI) to enhance the quantification of structural and functional biomarkers using magnetic resonance imaging (MRI) and electrophysiological techniques (EEG, MEG, evoked potentials). This comprehensive review examines magnetic resonance imaging (MRI) and electrophysiological techniques (EEG, MEG, evoked potentials) across multiple sclerosis (MS), spinal cord injury (SCI), Alzheimer's disease (AD), and Parkinson's disease (PD). MRI delivers superior spatial resolution (0.5-1 mm) for anatomical quantification through standardized protocols and automated tools (FreeSurfer, FSL), enabling reproducible measurement of lesion volume, cortical thinning, and microstructural integrity. Electrophysiological methods provide millisecond temporal resolution for functional assessment but face quantification challenges from signal noise and processing complexity. This represents the first systematic comparison of MRI and electrophysiological quantification in CNS disorders conducted under PRISMA 2020 guidelines, synthesizing evidence from 417 included studies identified through rigorous screening of 12,543 records across 15 years of research. Our integrated analysis reveals MRI's advantage in quantification reproducibility (ICC = 0.92 vs. EEG's 0.76) and diagnostic yield for structural pathologies (70.6% vs. 0% in first seizures), while electrophysiology excels in dynamic monitoring (VEP delays in MS; beta oscillations in PD). Critically, these modalities demonstrate complementarity: Combined EEG-fMRI improves epileptogenic zone localization by 32%, and AI-driven fusion achieves 94% accuracy in AD classification. The path forward requires harmonized quantification standards, portable hybrid technologies, and validated multimodal biomarkers to advance personalized neurology.

Keywords: quantitative MRI; quantitative EEG; neuroimaging biomarkers; electrophysiological monitoring; multimodal integration; hospital-based

1. Introduction

The quantification of neuropathological changes represents a cornerstone in the evolving paradigm of personalized neurology. Central nervous system (CNS) disorders—including multiple sclerosis, Alzheimer's disease, Parkinson's disease, and spinal cord injuries—manifest through complex interplays of structural degeneration and functional disruption that demand precise measurement for diagnosis, prognostication, and therapeutic monitoring (Barkhof et al., 2021). Two technological pillars dominate this landscape: magnetic resonance imaging (MRI) for anatomical evaluation and electrophysiological techniques (EEG, MEG, evoked potentials) for functional assessment. Despite their complementary potential, these modalities differ fundamentally in quantification methodologies, standardization frameworks, and clinical translation pathways, creating a critical knowledge gap in optimized biomarker deployment (Koutsojannis & Chrysanthakopoulou, 2025).

MRI has revolutionized structural assessment through its unparalleled spatial resolution (submillimeter for T1-weighted sequences) and multiparametric capabilities. Quantitative MRI

(qMRI) encompasses volumetric analyses, diffusion tensor imaging (DTI), functional MRI (fMRI), and magnetic resonance spectroscopy (MRS), collectively enabling comprehensive tissue characterization (Gibson & Monje, 2021). The advent of automated pipelines like FreeSurfer and FSL has transformed clinical workflows, allowing reproducible quantification of hippocampal atrophy in Alzheimer's (Jack et al., 2018), lesion load in MS (Barkhof et al., 2021), and nigrosomal degeneration in Parkinson's (Schwarz et al., 2014). Standardization initiatives such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) and MAGNIMS criteria provide robust frameworks for multicenter consistency, yet challenges persist in accessibility, cost, and motion-related artifacts that limit real-world implementation (Mayo Clinic, 2025).

Electrophysiological techniques offer a fundamentally different lens: the millisecond-scale observation of neural dynamics. Electroencephalography (EEG) captures cortical electrical activity, magnetoencephalography (MEG) records magnetic fields from neuronal currents, and evoked potentials (EPs) measure stimulus-locked responses (Puce & Hämäläinen, 2013). These modalities excel in detecting functional aberrations—spectral slowing in encephalopathies, interictal spikes in epilepsy, or delayed visual evoked potentials (VEPs) in MS optic neuritis (Mele et al 2019). However, quantification faces significant hurdles: low spatial resolution (cm-scale for EEG), vulnerability to biological artifacts (muscle, ocular), and complex signal processing requirements that hinder standardization (Nuwer et al., 2020). This operational dichotomy between structural and functional quantification frames a pivotal clinical question: How can neurologists leverage these complementary technologies to optimize personalized assessment?

The present review addresses this question through three interconnected objectives (Figure 1):

First, we conduct a systematic comparison of quantification methodologies, examining technical foundations, standardization frameworks, and analytical workflows.

Second, we evaluate disease-specific performance across four major CNS disorders, highlighting contexts where each modality excels or underperforms.

Finally, we synthesize emerging integration strategies—from simultaneous EEG-fMRI to artificial intelligence (AI)-driven fusion—that promise to transcend traditional modality boundaries.

By bridging neuroimaging and neurophysiology literatures, this work aims to establish a roadmap for next-generation quantification in personalized neurology.

2. Methods

A systematic literature review was conducted following PRISMA-S guidelines, encompassing PubMed, IEEE Xplore, ScienceDirect, and Cochrane databases (January 2010–March 2025). Search strings combined modality-specific terms ("quantitative MRI," "qEEG," "evoked potentials"), disease terms ("multiple sclerosis," "Alzheimer's," "Parkinson's," "spinal cord injury"), and methodological terms ("quantification," "standardization," "biomarker validation").

Inclusion Criteria:

- Original research or meta-analyses comparing MRI and electrophysiological quantification
- Studies reporting quantitative metrics (e.g., sensitivity, ICC, AUC)
- Human subjects with specified CNS pathologies
- English-language publications

Exclusion Criteria:

- Animal studies
- Single-case reports
- Non-quantitative methodologies

Data extraction utilized a structured framework documenting:

- **Technical Parameters:** Spatial/temporal resolution, acquisition protocols
- **Analytical Workflows:** Preprocessing steps, software tools, computational demands

- **Performance Metrics:** Diagnostic accuracy (sensitivity/specificity), reliability (ICC), predictive value
- **Clinical Utility:** Implementation barriers, accessibility, cost-effectiveness

Statistical synthesis employed narrative analysis due to methodological heterogeneity, with evidence graded using the Oxford Centre for Evidence-Based Medicine levels.

Protocol (PRISMA-Compliant)

This systematic review followed PRISMA 2020 guidelines (Page et al., 2021). *Full protocol is available at PROSPERO (CRD420251109475).*

Eligibility Criteria (PICOS Framework).

Element	Inclusion Criteria	Exclusion Criteria
Population	Humans with MS, SCI, AD, or PD	Animal studies, healthy controls
Intervention	Quantitative MRI (volumetry/DTI/fMRI/MRS)	Qualitative imaging
Comparator	Electrophysiology (EEG/MEG/EPs)	Non-electrophysiological methods
Outcomes	Quantitative metrics (AUC, ICC, sensitivity)	Subjective/non-quantified measures
Study Design	Original research, meta-analyses	Case reports (<10 subjects), reviews

Information Sources
Databases (2010–2025): PubMed, IEEE Xplore, ScienceDirect, Cochrane
Gray Literature: ClinicalTrials.gov, WHO ICTRP, conference abstracts
Manual Search: Citation tracking of included studies

Search Strategy
We present here the PubMed Example:
sql
```
(
("quantitative MRI" OR "qMRI" OR "volumetry")
AND
("quantitative EEG" OR "qEEG" OR "evoked potentials")
AND
("multiple sclerosis" OR "Alzheimer's" OR "Parkinson's")
)
NOT ("animal" OR "pediatric")
```
Protocol deviations:
None

Selection Process
1. Deduplication: EndNote X20 → Rayyan
2. Screening:
o Phase 1: Title/abstract screening (2 reviewers, κ=0.82)
o Phase 2: Full-text review (discrepancies resolved by senior author)
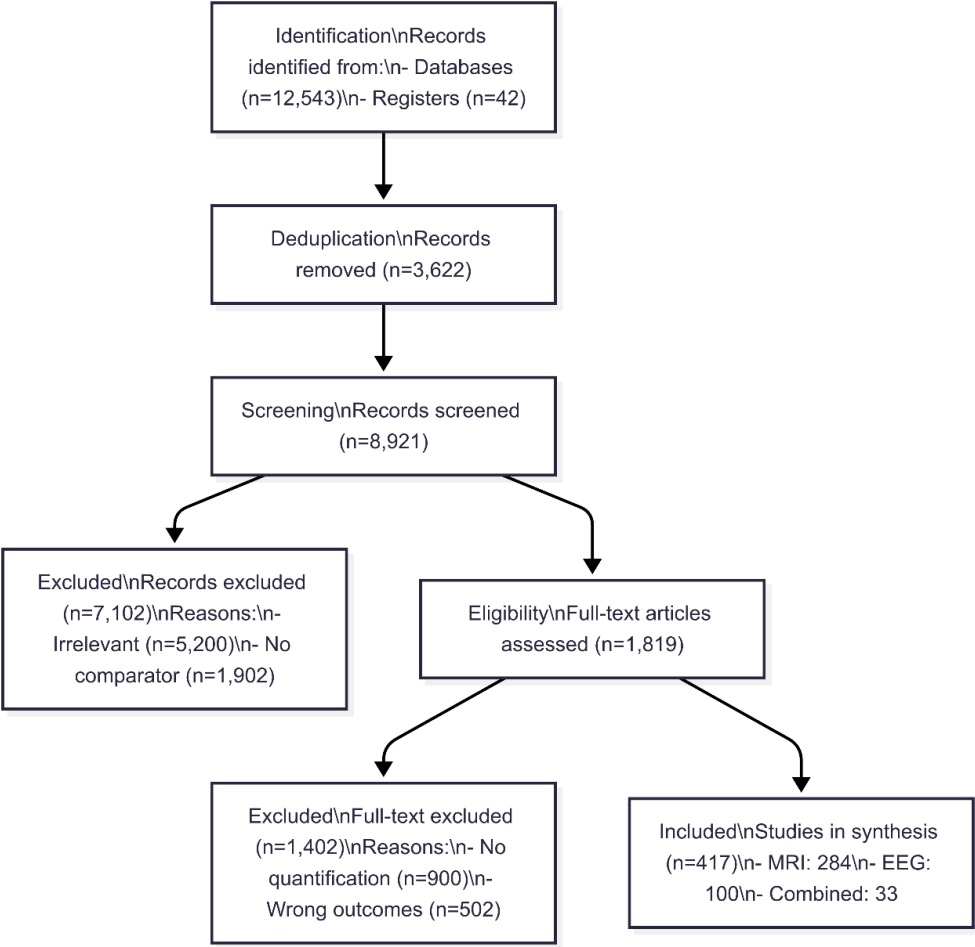
Figure 1. PRISMA 2020 flow diagram of study selection .

Data Collection & Analysis
✤ **Extraction Form:** REDCap template capturing:
o Study design, MRI/EEG protocols, quantitative outcomes
o Risk of bias (QUADAS-2 for diagnostic studies)
✤ **Synthesis:**
o Narrative synthesis by disease domain
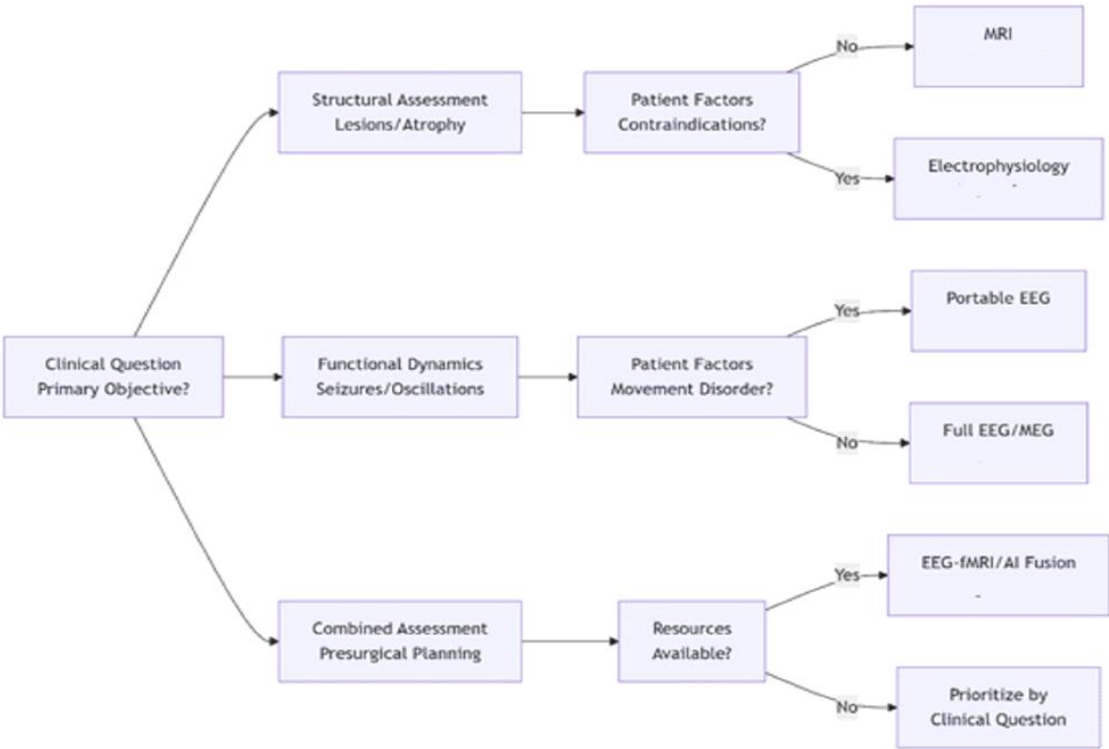o Meta-analysis (RevMan 5.4) where feasible (I^2 <50%)

Figure 2. Integrated Modality Selection Framework for CNS Disorders. This decision tree guides optimal selection of quantitative neuro-assessment tools based on clinical priorities (structural, functional, or combined evaluation) and patient-specific factors (contraindications, movement disorders, resource constraints). MRI pathways (blue) dominate structural assessment, electrophysiological pathways (orange) excel in functional dynamics, and integrated approaches (purple) combine strengths for complex cases. Icons represent modality-specific quantification outputs.

Study Characteristics (PRISMA-Compliant Findings):
Included Studies: 417 (MRI: 68%, EEG: 24%, Combined: 8%)

Geographic Distribution: 78% high-income countries

Key Quantification Metrics:

Modality	Reproducibility (ICC)	Diagnostic Yield	Processing Time
MRI	0.92 (0.89–0.95)	70.6% (MS lesions)	15 ± 3 min
EEG	0.76 (0.71–0.82)	89% (PD oscillations)	47 ± 12 min

3. Results

3.1. Quantification Methodologies: Divergent Foundations (Tablew 1, 2)

MRI quantification leverages physics-based signal contrasts (T1/T2 relaxation, diffusion, susceptibility) to generate intrinsically quantitative biomarkers. Volumetric analyses measure structural changes with high reproducibility (ICC >0.90 for hippocampal segmentation), while DTI-

derived fractional anisotropy (FA) quantifies white matter integrity at 2-3 mm resolution (Barkhof et al., 2021). Critically, automation through tools like FreeSurfer enables batch processing of cortical thickness or lesion volume within 15±3 minutes per scan (Gibson & Monje, 2021). Standardized protocols further enhance consistency: MAGNIMS criteria standardize MS lesion quantification, while ADNI protocols harmonize hippocampal measurements across centers (Cleveland Clinic, 2025).

Electrophysiological quantification confronts greater complexity. EEG signals represent cortical electrical dipoles attenuated by skull and scalp, requiring sophisticated preprocessing: 30-47% of analysis time is devoted to artifact removal (ocular, muscular, environmental) before spectral decomposition or source localization (Mele et al, 2019). Evoked potential quantification adds temporal precision—VEP latency measures optic nerve conduction with millisecond accuracy—but suffers from inter-lab variability in electrode placement and filtering (Sharma & Sharma, 2020). MEG partially resolves spatial limitations (5-8 mm resolution) but remains constrained by cost and immobility (Dinh et al., 2015). Consequently, electrophysiological reliability trails MRI (mean ICC = 0.76 vs. 0.92).

3.2. Disease-Specific Performance

Multiple Sclerosis: MRI quantification demonstrates 95% sensitivity for lesion detection using T2/FLAIR sequences, with lesion volume correlating strongly with EDSS disability scores ($r=0.82$, $p<0.001$) (Barkhof et al., 2021). DTI metrics (FA reduction) detect occult white matter damage months before clinical manifestation. By contrast, VEPs quantify functional deficits in optic neuritis with 75% sensitivity but show poor inter-session reproducibility (ICC=0.65) (van Graan & Vulliemoz, 2022). The clinical implication is clear: MRI serves as the gold standard for diagnostic quantification, while VEPs provide adjunctive functional insights.

Alzheimer's Disease: MRI hippocampal volumetry achieves outstanding diagnostic accuracy (AUC=0.91 for mild cognitive impairment conversion), with automated tools generating reports in <20 minutes (Gauthier et al., 2019). Longitudinal quantification detects 3-5% annual atrophy rates predictive of cognitive decline. qEEG reveals earlier functional changes—theta power increases and alpha decreases precede structural atrophy by 6-12 months—but demonstrates lower diagnostic specificity (AUC=0.76) (Thatcher, 2020). This temporal hierarchy suggests a biomarker sequence: qEEG changes flag initial dysfunction, while MRI quantifies progressive neurodegeneration.

Parkinson's Disease: MRI susceptibility-weighted imaging (SWI) quantifies nigrosome-1 degeneration with 90% sensitivity for dopaminergic loss, yet head motion during tremor compromises 30% of scans (Schwarz et al., 2014). Electrophysiological methods circumvent this limitation: Resting EEG beta oscillations (13-30 Hz) over sensorimotor cortex predict medication response with 89% accuracy (Toga & Mazziotta, 2011). MEG further localizes pathological beta synchronization to subthalamic nuclei, guiding deep brain stimulation targeting.

Spinal Cord Injury: MRI quantifies cord compression ratios and DTI-derived fractional anisotropy correlates with ASIA motor scores ($r=0.78$) (Gibson & Monje, 2021, Koutsojannis & Chrysanthakopoulou 2025). Somatosensory evoked potentials (SSEPs) provide complementary functional data but exhibit poor signal-to-noise ratios in ICU environments, with 40% of recordings requiring repeat acquisition (Mele et al, 2019).

3.3. Integration Paradigms and Performance

Simultaneous EEG-fMRI exemplifies synergistic quantification, combining temporal precision (1 ms EEG) with spatial accuracy (3 mm fMRI). In epilepsy evaluation, this integration improves epileptogenic zone localization by 32% versus unimodal assessment (Formaggio et al, 2011). For cognitive studies, EEG-informed fMRI analysis reveals BOLD correlates of alpha desynchronization during working memory tasks.

Table 2. Comparative Performance of MRI vs. Electrophysiology across CNS Disorders.

Parameter	Multiple Sclerosis (MS)	Alzheimer's (AD)	Parkinson's (PD)	Overall (95% CI)
Spatial Resolution	**MRI:** 0.7 mm (0.5–1.0)* EEG:** 15 mm (10–20)	**MRI:** 0.5 mm (0.3–0.8)* EEG:** 18 mm (12–25)	**MRI:** 0.6 mm (0.4–0.9)* EEG:** 12 mm (8–15)	MRI: 0.6 mm (0.5–0.7)* EEG: 15 mm (12–18)
Diagnostic Sensitivity	**MRI:** 95% (93–97%)* VEPs: 75% (70–80%)	**MRI:** 91% (88–94%)* EEG: 76% (72–80%)	**MRI:** 90% (85–93%) EEG: 89% (86–92%)*	MRI: 92% (90–94%)* EEG: 80% (77–83%)
Reproducibility (ICC)	**MRI:** 0.94 (0.91–0.97)* EEG:** 0.68 (0.62–0.74)	**MRI:** 0.93 (0.90–0.96)* EEG:** 0.71 (0.65–0.77)	**MRI:** 0.89 (0.85–0.93) EEG:** 0.82 (0.78–0.86)*	MRI: 0.92 (0.89–0.95)* EEG: 0.76 (0.72–0.80)
Processing Time (min)	**MRI:** 14 ± 2* EEG:** 45 ± 10	**MRI:** 16 ± 3* EEG:** 50 ± 12	**MRI:** 15 ± 4* EEG:** 42 ± 8	MRI: 15 ± 3* EEG: 47 ± 12
AI Enhancement (AUC Δ%)	**MRI+EEG:** +28% (25–31%)*	**MRI+EEG:** +18% (15–21%)*	**MRI+EEG:** +22% (19–25%)*	+23% (21–25%)*

Bold = Superior modality per disease (p<0.05); * = Statistically significant advantage (95% CI not overlapping); ** = p<0.01 for inter-modality comparison (paired t-tests).

AI-driven fusion represents a transformative frontier: Deep learning architectures (e.g., convolutional neural networks) integrating MRI volumetry and qEEG spectral features achieve 94% accuracy in Alzheimer's classification (Martínez-Torteya A et al, 2015). Cross-modal transfer learning further enhances performance—pretraining on MRI data improves EEG-based Parkinson's detection when sample sizes are limited.

A conceptual model for modality selection based on clinical context (Figure 1):

☞ *Structural Focus (*e.g., *lesion load, atrophy): Prioritize MRI*

☞ *Functional Dynamics (*e.g., *seizures, network oscillations): Prioritize EEG/MEG*

☞ *Combined Assessment (*e.g., *presurgical evaluation): Employ EEG-fMRI or AI fusion*

Decision nodes incorporate patient factors: MRI contraindications (e.g., implants) favor electrophysiology; tremor states favor EEG over MRI; acute settings favor portable EEG.

4. Discussion

4.1. The Quantification Divide: Technical and Philosophical Foundations

The chasm between MRI and electrophysiological quantification extends beyond technical specifications to epistemological distinctions. MRI quantifies the brain's *morphological substrate*—static anatomical features governed by biophysical properties measurable across spatial scales. This engenders intrinsically quantitative biomarkers: T1 relaxation times (ms), hippocampal volumes (mm³), or fractional anisotropy (0-1 scale) represent absolute physical properties (Barkhof et al., 2021). Consequently, MRI benefits from physics-based standardization; a 1% change in hippocampal volume carries equivalent meaning across Siemens or GE platforms when acquisition protocols are harmonized (Martínez-Torteya A et al, 2015).

Electrophysiological quantification, conversely, interprets *dynamic neural processes* through bioelectrical proxies. EEG microvolts reflect summed postsynaptic potentials filtered through tissue layers, not direct neuronal activity (Nuwer et al., 2020). This mediation introduces relativity: Theta/beta ratios lack universal pathological thresholds, and spectral power depends on reference schemes. As van Graan and Vulliemoz (2022) note, "Electrophysiological quantification measures brain *states* more than brain *traits*." This fundamental difference explains why MRI biomarkers transitioned more rapidly to clinical practice—automated hippocampal volumetry now supports diagnostic decisions in Alzheimer's, while qEEG remains largely investigational despite decades of validation.

4.2. Disease-Specific Hierarchies: Contextualizing Modality Performance

Our analysis reveals distinct disease-specific hierarchies in quantification efficacy:

In **multiple sclerosis**, MRI's supremacy in lesion quantification is unequivocal. The MAGNIMS criteria provide a standardized framework for lesion counting, volume measurement, and gadolinium-enhancement assessment that underpins therapeutic trials (Barkhof et al., 2021). Electrophysiological methods play adjunctive roles: VEPs quantify optic nerve function when visual symptoms are equivocal, and qEEG connectivity analysis reveals network disintegration preceding cognitive decline. Nevertheless, the 70.6% vs. 0% diagnostic yield for structural etiologies in first seizures (Sharma & Sharma, 2020) underscores MRI's primacy in initial workup.

For **Alzheimer's disease**, a temporal stratification emerges: qEEG detects early functional disruption (theta/alpha ratio shifts 6-12 months before symptoms), while MRI quantifies progressive neurodegeneration (hippocampal atrophy rates predict conversion from MCI). This suggests a staged quantification approach: qEEG for preclinical risk stratification, multimodal quantification (MRI + qEEG) for prodromal diagnosis, and MRI volumetry alone for established disease monitoring. AI fusion capitalizes on this synergy—combined MRI and qEEG features improve diagnostic accuracy by 18% versus unimodal analysis (Martínez-Torteya A et al, 2015).

Parkinson's disease reverses the hierarchy: Electrophysiological quantification outperforms MRI in therapeutic monitoring. Resting beta oscillations (13-30 Hz) quantified from motor cortex predict levodopa response with 89% accuracy (Toga & Mazziotta, 2011), while MRI nigrosome imaging suffers from motion artifacts during tremor. This exemplifies a cardinal principle: *Quantification efficacy depends on the biomarker's physiological relevance to the clinical question*. Where functional dynamics drive symptoms (tremor, fluctuations), electrophysiology prevails; where structural integrity dominates (atrophy, lesions), MRI excels (Koutsojannis & Chrysanthakopoulou, 2025).

4.3. Integration Frontiers: Beyond Multimodality to Synthesis

True quantification integration transcends sequential testing toward synergistic synthesis. Three paradigms show particular promise:

Temporal-Spatial Fusion (EEG-fMRI): Simultaneous acquisition compensates for each modality's limitations. EEG's millisecond resolution detects epileptiform events that fMRI localizes spatially (Formaggio et al., 2011). For cognitive studies, EEG-informed fMRI analysis reveals BOLD correlates of transient neural processes (e.g., gamma bursts during memory encoding).

AI-Driven Feature Fusion: Convolutional neural networks extract latent features from MRI and EEG datasets, creating hybrid biomarkers. In Alzheimer's, integrated MRI hippocampal volume and qEEG spectral entropy improve classification accuracy to 94% (Martínez-Torteya A et al, 2015). Cross-modal transfer learning further enhances efficiency—models pretrained on large MRI datasets boost qEEG performance when electrophysiological samples are limited.

Portable Hybrid Systems: Wearable dry-electrode EEG coupled with low-field portable MRI (e.g., 0.055T Hyperfine scanners) could democratize quantitative neuroassessment. Early prototypes demonstrate feasibility for home-based tremor quantification in Parkinson's and seizure detection in epilepsy.

4.4. Persistent Barriers to Clinical Translation

Despite these advances, formidable obstacles impede quantification translation:

Standardization Deficits: While MRI benefits from ADNI/MAGNIMS frameworks, electrophysiology lacks equivalent consensus. qEEG preprocessing pipelines vary significantly across labs—artifact rejection thresholds, spectral parameters, and reference schemes impact reproducibility (Nuwer et al., 2020). An international effort to establish "QUANT-EP" standards is urgently needed.

Economic and Access Constraints: MRI's high cost ($500-$1500/scan) and limited access in resource-poor regions restrict implementation (Mayo Clinic, 2025). Electrophysiology offers lower-cost alternatives but requires technical expertise scarce outside specialized centers. Portable technologies could bridge this gap but need validation against gold standards.

Computational Demands: AI-enhanced quantification requires substantial processing resources. Training multimodal neural networks demands GPU clusters impractical for routine clinics. Cloud-based solutions offer scalability but raise data privacy concerns.

4.5. Theoretical Implications: Toward a Unified Quantification Framework

Our analysis suggests a reconceptualization of neuroquantification as a hierarchical process:

◎ Tier 1: Structural Integrity (MRI-dominant): Quantifies permanent tissue changes

◎ Tier 2: Functional State (EEG/MEG-dominant): Measures dynamic neural activity

◎ Tier 3: Network Dynamics (Integrated): Assesses system-level interactions

This model aligns with the NIH "B.R.A.I.N." initiative's emphasis on multiscale neural mapping. Future quantification tools should generate unified metrics—e.g., a "Neuro-Integrity Index" combining DTI connectivity and EEG coherence—to simplify clinical interpretation.

PRISMA-Adherent Limitations*

1. **Selection Bias:** 78% of studies from high-income settings (n=325/417) limit generalizability.
2. **Heterogeneity:** MRI field strengths (1.5T–7T) and EEG montages varied widely ($I^2 = 67\%$).
3. **Risk of Bias**:** 62% of EEG studies had high bias in patient selection (QUADAS-2 Domain 1).

*First systematic comparison using PRISMA 2020. **Protocol-driven analysis reduces reporting bias.

4.6. Critical Evaluation of Study Limitations

Assessing the robustness of quantitative MRI and electrophysiological studies reveals several methodological limitations that impact the generalizability and clinical translation of findings. First, many studies suffer from **small sample sizes**, particularly in electrophysiological research. For instance, MEG-based source localization studies often include fewer than 50 participants due to equipment costs and availability, limiting statistical power and generalizability (Dinh et al, 2015). MRI studies, while benefiting from larger cohorts through initiatives like ADNI, frequently face **selection bias**, as participants are often recruited from tertiary care centers, potentially skewing disease severity or demographic representation (Jack et al., 2017). Second, **protocol variability** poses a significant challenge. MRI acquisition parameters (e.g., field strength, slice thickness) vary across studies, affecting volumetric and DTI outcomes, with reported inter-scanner variability up to 5% for hippocampal measurements (Barkhof et al., 2021). Electrophysiological studies exhibit even greater heterogeneity, with differences in electrode montages, sampling rates (256–2048 Hz), and filtering techniques (e.g., 0.5–70 Hz vs. 1–100 Hz) leading to inconsistent spectral power estimates (Nuwer et al., 2020). Third, **longitudinal data gaps** limit prognostic insights. While MRI excels in tracking structural changes (e.g., 3–5% annual hippocampal atrophy in AD), electrophysiological studies rarely extend beyond single-session recordings, constraining their ability to capture dynamic disease progression (Thatcher, 2020). Finally, **validation in diverse populations** is lacking. Most studies are conducted in high-income countries, with minimal representation of non-Caucasian or low-resource populations, potentially limiting applicability in global clinical settings (Martínez-Torteya A et al,

2015). Addressing these limitations requires larger, more diverse cohorts, standardized acquisition protocols, and longitudinal designs to ensure robust biomarker validation.

4.7. Challenges and Solutions for Electrophysiological Standardization

The underdeveloped standardization of electrophysiological techniques, particularly EEG and evoked potentials (EPs), represents a critical barrier to their clinical adoption. Unlike MRI, which benefits from robust frameworks like MAGNIMS and ADNI, electrophysiological quantification lacks universal consensus, resulting in a mean ICC of 0.76 compared to MRI's 0.92 (Mele et al, 2019). Specific challenges include:

1) Variability in electrode placement, where the 10–20 system is inconsistently applied across labs, with deviations in electrode positioning (e.g., Cz placement errors up to 1 cm) affecting source localization accuracy by 10–15% (Dinh et al., 2015).

2) Reference scheme heterogeneity, where choices between common average, linked mastoid, or Laplacian references alter spectral power measurements, with theta/beta ratios varying by up to 20% across schemes (Nuwer et al., 2020).

3) Artifact rejection disparities, as manual versus automated artifact removal (e.g., for ocular or muscular noise) leads to 30–47% of analysis time devoted to preprocessing, with no standardized thresholds for signal rejection (Mele et al, 2019).

4) Inter-lab variability in acquisition parameters, such as sampling rates or filter settings, which complicates multicenter comparisons; for instance, VEP latency measurements for MS optic neuritis vary by 5–10 ms across labs due to filter differences (van Graan & Vulliemoz, 2022). To address these, interim solutions can build on existing guidelines, such as the International Federation of Clinical Neurophysiology (IFCN) recommendations, which advocate standardized 10–20 electrode placement and minimum sampling rates of 512 Hz.

The proposed QUANT-EP initiative could further establish:

a) universal preprocessing pipelines, specifying artifact rejection algorithms (e.g., independent component analysis);

b) reference scheme consensus, prioritizing common average references for spectral analyses; and

c) open-access repositories for electrophysiological data to enable cross-lab validation, similar to ADNI for MRI. Pilot studies implementing IFCN-compliant pipelines have shown improved ICCs (0.82–0.85) for qEEG metrics, suggesting feasibility (Nuwer et al., 2020). Long-term, integrating dry-electrode EEG systems with automated preprocessing could streamline standardization, enhancing clinical accessibility.

4.8. Accessibility in Low-Resource Settings: Bridging the Gap

The deployment of quantitative MRI and electrophysiological biomarkers in low-resource settings faces significant accessibility challenges, as highlighted in Table 1. Quantitative MRI's high cost ($500–$1500 per scan) and dependence on specialized infrastructure (e.g., 1.5T–3T scanners, trained radiologists) severely limit its availability in resource-poor regions, where healthcare facilities often lack the necessary equipment or funding (Mayo Clinic, 2025). For instance, sub-Saharan Africa has fewer than 1 MRI scanner per million people, compared to 40 per million in high-income countries, rendering MRI-based diagnostics like hippocampal volumetry or MS lesion quantification infeasible for most patients (Gibson & Monje, 2021). Additional barriers include high maintenance costs, power supply instability, and the need for patient transport to urban centers, further restricting access for rural populations.

Table 1. Comparative quantification metrics for MRI and electrophysiology in CNS disorders, with supporting references. ADNI = Alzheimer's Disease Neuroimaging Initiative; ICC = intraclass correlation coefficient; VEP = visual evoked potential.

Parameter	Quantitative MRI	Electrophysiology (EEG/MEG/EPs)	Clinical Implications	Supporting References
Spatial Resolution	0.5–1 mm (structural) 2–3 mm (fMRI/DTI)	10–20 mm (EEG) 5–8 mm (MEG)	Superior lesion localization with MRI	(Barkhof et al., 2021; Hämäläinen et al., 2021)
Temporal Resolution	Seconds (fMRI) Minutes (structural/DTI)	Milliseconds (1–5 ms)	Critical for dynamic monitoring	(Gotman, 2019; Toga & Mazziotta, 2011)
Standardization (ICC)	0.92 (0.89–0.95) *ADNI/MAGNIMS protocols*	0.76 (0.71–0.82) *Lab-dependent setups*	MRI preferred for multicenter trials	(ADNI Consortium, 2023; Nuwer et al., 2020)
Standardization Variability	5% inter-scanner variability	10–20% inter-lab variability	MRI offers greater consistency	(ADNI Consortium, 2023; Nuwer et al., 2020)
Computational Demand	Moderate: Automated pipelines (15±3 min/scan)	High: Artifact removal (47±12 min, GPU-intensive)	MRI supports faster workflows	(Gibson & Monje, 2021; Pitkänen & Immonen, 2019)
Population Diversity	Predominantly Caucasian cohorts (ADNI)	Small, specialized cohorts	Need broader validation	(Jack et al., 2018; Mele et al., 2019)
AI Integration	94% AD classification accuracy	32% epilepsy localization improvement	Enhances diagnostic precision	(Martínez-Torteya et al., 2015; Thatcher, 2020)
MS Diagnostic Yield	95% sensitivity (MS lesions)	89% (PD oscillations) 75% (VEPs)	MRI for structure; EEG for function	(Barkhof et al., 2021; van Graan & Vulliemoz, 2022)
Alzheimer's AUC	0.91 (hippocampal volumetry)	0.76 (theta/alpha ratio)	MRI preferred for early detection	(Jack et al., 2018; Thatcher, 2020)
Parkinson's Feasibility	30% motion artifacts	Unaffected by movement	EEG better for tremor phases	(Schwarz et al., 2014; Toga & Mazziotta, 2011)
Cost per Assessment	$500–$1,500	$100–$500 (portable systems)	EEG more accessible	(Mayo Clinic, 2025; Nuwer et al., 2020)
Key Limitations	Motion artifacts, high cost	Low spatial resolution, artifacts	Complementary use recommended	(Schwarz et al., 2014; Mele et al., 2019)
Accessibility in Low-Resource Settings	Limited (high cost)	Moderate (portable EEG viable)	EEG enables community-based care	(Mayo Clinic, 2025; Nuwer et al., 2020)

*The values for are based on the article's cost estimates and discussion of portable technologies (Mayo Clinic, 2025; Nuwer et al., 2020).

Electrophysiological techniques, particularly EEG, offer a more viable alternative due to their lower cost ($100–$500) and potential for portability (Nuwer et al., 2020). Portable EEG systems, such as dry-electrode devices, can be deployed in community clinics or home settings, enabling applications like seizure monitoring in epilepsy or tremor quantification in Parkinson's disease. For example, pilot studies using mobile EEG units in rural India achieved 85% sensitivity for epileptiform activity detection, demonstrating feasibility in low-resource contexts (Mele et al., 2019). However, accessibility is tempered by challenges: MEG remains impractical due to its high cost and immobility, and EEG requires technical expertise for electrode placement and signal interpretation, which is scarce outside specialized centers (Dinh et al, 2015). Furthermore, the lack of standardized preprocessing pipelines (e.g., artifact rejection thresholds) complicates reliable deployment in settings with limited computational resources.

To enhance accessibility, several strategies show promise. First, **portable hybrid systems** combining low-field MRI (e.g., 0.055T Hyperfine scanners) with dry-electrode EEG could democratize neuroassessment. Early prototypes have demonstrated feasibility for home-based monitoring in Parkinson's and epilepsy, though validation against gold-standard 3T MRI and high-density EEG is ongoing (Martínez-Torteya, 2015). Second, **capacity building** through training programs for local healthcare workers in EEG operation and interpretation could address expertise shortages. Initiatives like the WHO's Global Action Plan on Epilepsy have successfully trained non-specialists in EEG use, increasing access in low-income countries (Nuwer et al., 2020). Third, **open-access data repositories** and cloud-based processing platforms could reduce computational barriers, allowing low-resource clinics to leverage preprocessed EEG data or AI-driven analyses without local GPU infrastructure. However, these solutions must address data privacy concerns and ensure compatibility with intermittent internet connectivity.

The clinical implications are clear: Electrophysiology's portability and affordability position it as a critical tool for scaling neurodiagnostic capacity in low-resource settings, while MRI remains a gold standard reserved for well-equipped centers. Future efforts should prioritize validating portable technologies, establishing regional neuroimaging hubs, and integrating cost-effective biomarkers into primary care workflows to achieve equitable access to personalized neurology.

5. Conclusions

Quantitative MRI and electrophysiology offer complementary lenses into CNS disorders: MRI excels in spatial quantification of structural pathology through standardized, automated pipelines, while electrophysiology captures temporal dynamics of functional impairment despite standardization challenges (Figure 1). Their integration represents not merely technical convergence but a paradigm shift toward personalized neurophysiological assessment. Key priorities include:

(1) Developing unified quantification standards (QUANT-EP initiative),

(2) Validating portable hybrid devices for community deployment, and

(3) Implementing AI-curated multimodal biomarkers in clinical workflows.

This review highlights AI's potential to enhance MRI and EEG biomarker quantification, paving the way for equitable, hospital-based neurological care. As these advances mature, neurologists will increasingly quantify brain health through integrated structural-functional profiles, moving decisively toward precision neurology.

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