Review

Advancing Precision Neurology and Wearable Electrophysiology: The Pivotal Role of Medical Physicists in Signal Processing, AI, and Prognostic Modeling

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Advancing Precision Neurology and Wearable Electrophysiology: The Pivotal Role of Medical Physicists in Signal Processing, AI, and Prognostic Modeling

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Abstract

Medical physicists are transforming physiological measurements and electrophysiological applications by addressing challenges like motion artifacts and regulatory compliance through advanced signal processing, artificial intelligence (AI), and statistical rigor. Their innovations in wearable electrophysiology achieve 8–12 dB signal-to-noise ratio (SNR) improvements in EEG, 60% motion artifact reduction, and 94.2% accurate AI-driven arrhythmia detection at 12 μW power. In precision neurology, machine learning (ML) with evoked potentials (EPs) predicts spinal cord injury (SCI) recovery and multiple sclerosis (MS) progression with 79.2% accuracy of retrospective data from 560 SCI/MS patients. By integrating multimodal data (EPs, MRI), developing quantum sensors, and employing federated learning, they enhance diagnostic precision and prognostic accuracy. Clinical applications span epilepsy, stroke, cardiac monitoring, and chronic pain management, reducing diagnostic errors by 28% and optimizing treatments like deep brain stimulation (DBS). Embedding medical physicists in standardization efforts is critical to overcoming barriers like quantum sensor power consumption, advancing personalized, evidence-based healthcare.

Keywords: medical physics; wearable electrophysiology; precision neurology; signal processing; machine learning; electroencephalography

Introduction

Physiological measurements, including wearable electrophysiology and evoked potentials (EPs), are pivotal for diagnostics and personalized medicine, enabling continuous monitoring and prognostic assessment. Wearable electrocardiography (ECG) and electroencephalography (EEG) face motion artifacts (50–500 μV noise), while EPs for SCI and MS require precise prognostic tools (European Federation of Organisations for Medical Physics [EFOMP], 1999; Koutsojannis & Chrysanthakopoulou, 2025). Medical physicists address these challenges through expertise in signal processing, AI, uncertainty quantification, and statistical validation, delivering reliable data for arrhythmias, epilepsy, and neurological disorders (International Atomic Energy Agency [IAEA], 1996). Their work achieves 8–12 dB SNR improvements in EEG, 94.2% accurate AI-driven diagnostics, and 79.2% accurate EP-based ML models for SCI/MS prognosis (Koutsojannis & Chrysanthakopoulou, 2025). This article explores their contributions, advocating for their integration into device development and standardization to advance precision neurology and wearable medical technology.

Pathophysiological Framework: Linking EPs to Neurological Disorders

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SCI and MS impair neural conduction through demyelination, inflammation, and axonal damage, making EPs critical biomarkers (Kakulas, 2004; Compston & Coles, 2008). In SCI, trauma induces oligodendrocyte apoptosis, reducing myelin and prolonging EP latencies (e.g., N20, P40), while inflammation (TNF-α, IL-6) reduces amplitudes (Curt & Dietz, 1999). Axonal transection results in absent amplitudes, signaling irreversible loss (Kakulas, 2004). In MS, autoimmune myelin attacks cause multifocal demyelination, detected by prolonged SSEP latencies, with chronic inflammation reducing MEP amplitudes (Leocani & Comi, 2008). Impaired remyelination leads to persistent EP abnormalities (Compston & Coles, 2008). Medical physicists leverage EPs to quantify these processes, enabling ML models to predict SCI recovery (ASIA scale) and MS progression (EDSS) with 79.2% accuracy (Koutsojannis & Chrysanthakopoulou, 2025).

The Expertise of Medical Physicists and Biophysicists

Medical physicists and biophysicists integrate physics, mathematics, biology, statistics, and computational intelligence to develop validated physiological measurement technologies (EFOMP, 1999). They transform noisy biosignals into clinical insights, spanning wearable ECG, EEG, and EP-based diagnostics emphasizing gaps in **real-time prognostic tools.**

In wearable electrophysiology, they achieve 8–12 dB SNR improvements in EEG using wavelet-based denoising, outperforming conventional filters by 2–4 times (Chen et al., 2023). Ag/AgCl nanostructured dry electrodes reduce impedance from 50–100 kΩ to <5 kΩ, enabling reliable ambulatory monitoring (Norton et al., 2015). Biophysicists develop 1D convolutional neural networks (CNNs), achieving 94.2% accuracy in arrhythmia detection at 12 μW, supporting week-long monitoring on a 100mAh battery (Ravì et al., 2016). In precision neurology, they design EP-based ML models, integrating SSEP latency and MEP time series to predict SCI/MS outcomes with 79.2% accuracy (Koutsojannis & Chrysanthakopoulou, 2025). Their multidisciplinary expertise ensures precision and clinical relevance.

Precision in Measurement Techniques

Precision is critical in electrophysiological applications, where subtle signal variations indicate conditions like seizures, arrhythmias, or neurological deficits (EFOMP, 1999). Medical physicists employ wavelet packet decomposition (WPD) with 6-level Daubechies-4 transforms and adaptive thresholding ($Tj = \sigma j\sqrt{(2\ln Nj)}$), reducing motion artifacts by 60% compared to finite impulse response (FIR) filters ($p < 0.01$) (Chen et al., 2023). This enables ambulatory EEG and ECG monitoring, detecting epileptiform spikes or arrhythmic patterns with high fidelity.

Nanostructured Ag/AgCl dry electrodes lower noise floors from 5–10 μV to 0.8–1.2 μV, supporting 72-hour epilepsy monitoring with <5% data loss versus 30–40% in conventional systems (Norton et al., 2015). Calibration to IEC 60601-2-47 ensures RR-interval uncertainties of ±2.8 ms, outperforming commercial devices (±5 ms) (IEC, 2021). For EPs, precise SSEP latency measurements (e.g., N20, P40) correlate with demyelination, enhancing prognostic accuracy in SCI/MS (Koutsojannis & Chrysanthakopoulou, 2025). These advancements support confident clinical decision-makin

Wavelet Packet Decomposition Implementation

WPD decomposes EEG signals into sub-bands, isolating motion artifacts (0.5–4 Hz) from neural signals (8–30 Hz). The algorithm uses a Daubechies-4 wavelet, applying 6-level decomposition and adaptive thresholding to reconstruct artifact-free signals. The process achieves 8–12 dB SNR improvements, critical for epilepsy monitoring.

Algorithm: Wavelet Packet Decomposition for EEG Denoising

Input: Raw EEG signal x(t), sampling rate fs

Output: Denoised EEG signal xd(t)

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1. Initialize Daubechies-4 wavelet (db4)
2. Perform 6-level WPD: decompose x(t) into sub-bands Wj,k
3. For each sub-band j,k:
   a. Compute variance σj = sqrt(mean(Wj,k^2))
   b. Set threshold Tj = σj * sqrt(2 * ln(Nj)) where Nj is sub-band length
   c. Apply soft thresholding: Wj,k = sign(Wj,k) * max(|Wj,k| - Tj, 0)
4. Reconstruct signal xd(t) using inverse WPD
5. Return xd(t)

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Adaptive Noise Cancellation for ECG

Adaptive noise cancellation (ANC) removes motion artifacts in ECG using a reference signal (e.g., accelerometer data). The adaptive filter minimizes the error (e(n) = s(n) - y(n)), where (s(n)) is the noisy ECG and (y(n)) is the filtered noise estimate, achieving 70% artifact reduction (Zhang et al., 2023).

Algorithm: Adaptive Noise Cancellation for ECG
Input: Noisy ECG s(n), reference noise r(n)
Output: Clean ECG e(n)

1. Initialize filter weights w(0) = 0
2. For each sample n:
   a. Compute filter output: y(n) = w(n) * r(n)
   b. Compute error: e(n) = s(n) - y(n)
   c. Update weights: w(n+1) = w(n) + μ * e(n) * r(n)
3. Return e(n)

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Uncertainty Calculations and Statistical Rigor

Physiological measurements face variability from biological, environmental, and instrumental sources. Medical physicists apply the Guide to the Expression of Uncertainty in Measurement (GUM)

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framework, achieving ±2.8 ms precision in ECG RR-intervals (JCGM, 2008). Bayesian inference and Monte Carlo simulations provide robust confidence intervals (IAEA, 1996).

In EEG, uncertainty quantification ensures accurate spectral edge frequency calculations, meeting IEC 60601-2-26 standards (IEC, 2021). In positron emission tomography (PET), statistical models quantify tracer uptake uncertainties (Wayne State University, 2023). Monte Carlo dropout estimates uncertainty in neural networks for EEG classification by applying dropout at inference, generating multiple predictions. For a CNN classifying ictal patterns, the variance of (T) predictions quantifies uncertainty, achieving 5.1% false positives (Beniczky et al., 2022).

Algorithm: Monte Carlo Dropout for EEG Uncertainty

Input: EEG data x, trained CNN M, dropout rate p

Output: Prediction y, uncertainty σ

1. Initialize empty lists Y, V
2. For t = 1 to T:
   a. Apply dropout to M with rate p
   b. Predict yt = M(x)
   c. Append yt to Y
3. Compute mean y = mean(Y)
4. Compute variance σ = var(Y)
5. Return y, σ

For EPs, uncertainty frameworks validate predictors like SSEP amplitude, correlating with MRI fractional anisotropy (r≈0.3–0.5) in SCI (Koutsojannis & Chrysanthakopoulou, 2025; Szynal et al., 2020). This rigor supports regulatory compliance and clinical trust.

Computational Intelligence in Physiological Measurements

Computational intelligence enhances physiological measurements by processing complex datasets. Medical physicists deploy 1D CNNs (68KB quantized) on wearables, achieving 94.2% accuracy in arrhythmia detection with 12 μW power, enabling week-long monitoring (Ravì et al., 2016). The CNN architecture includes:

```
# Pseudo-code for 1D CNN for Arrhythmia Detection
model = Sequential()
model.add(Conv1D(filters=32,       kernel_size=5,       activation='relu',
input_shape=(128, 1)))
model.add(MaxPooling1D(pool_size=2))
model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(5, activation='softmax'))  # 5 arrhythmia classes
model.compile(optimizer='adam',           loss='categorical_crossentropy',
metrics=['accuracy'])
```

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In EEG, edge-AI detects ictal patterns with a 5.1% false positive rate versus 8.2% in hospital systems, reducing latency to 8 seconds (Beniczky et al., 2022). Federated learning enables privacy-preserving multicenter validation:

```
# Pseudo-code for Federated Learning Workflow
def federated_train(local_models, global_model):
    global_weights = global_model.get_weights()
    for client in clients:
        local_model = local_models[client]
        local_model.train_on_local_data()
        local_weights = local_model.get_weights()
        global_weights = aggregate_weights(global_weights, local_weights,
client_weight)
    global_model.set_weights(global_weights)
    return global_model
```

In precision neurology, ML integrates EPs with imaging, predicting SCI/MS outcomes with 79.2% accuracy (Koutsojannis & Chrysanthakopoulou, 2025). In functional MRI, deep learning corrects motion artifacts in real time, enhancing neural signal detection (Caruana et al., 2022).

Federated Learning for EP-Based ML Models

Federated learning enables privacy-preserving ML model training across institutions, critical for scaling EP-based prognostic models. Each site trains a local model on EP data (e.g., SSEP latency, MEP amplitude), sharing only model weights with a central server for aggregation. This approach achieves 79.2% accuracy while complying with GDPR and HIPAA (Rieke et al., 2020).

Algorithm: Federated Learning for EP-Based ML
Input: EP datasets Di at K sites, global model M0
Output: Global model M*

1. Initialize global model M0 with random weights
2. For each round t = 1 to T:
   a. For each site k = 1 to K:
      i. Train local model Mk on Di using SGD
      ii. Send weight updates ΔWk to central server
   b. Aggregate weights: Wglobal = sum(ΔWk) / K
   c. Update M0 with Wglobal
3. Return final global model M*

Federated learning reduces data-sharing barriers, enhancing model generalizability for SCI/MS prognosis (Koutsojannis & Chrysanthakopoulou, 2025).

Explainable AI for EP-Based Models

Explainable AI (XAI) enhances trust in EP-based ML models. SHAP values quantify feature contributions (e.g., SSEP latency), revealing that latency accounts for 42% of SCI prognosis accuracy (Lundberg et al., 2020).

 doi:10.20944/preprints202508.0961.v1

Algorithm: SHAP for EP-Based ML
Input: EP data x, ML model M
Output: SHAP values φ

1. Initialize background dataset Xb
2. For each feature i in x:
   a. Compute predictions for all coalitions S ⊆ Xb
   b. Calculate φi = sum[weight(S) * (M(S ∪ i) - M(S))]
3. Return φ

Imaging Correlations: Complementing EPs with Structural Insights

Imaging modalities enhance EP-based prognostics by providing structural insights (Szynal et al., 2020; Invernizzi et al., 2011). T2-weighted MRI reveals edema in SCI and demyelinating plaques in MS, correlating with EP abnormalities (Koutsojannis & Chrysanthakopoulou, 2025). Diffusion tensor imaging (DTI) shows reduced fractional anisotropy (FA), indicating axonal disruption, aligning with SSEP amplitude reductions (r≈0.3–0.5) (Okimatsu et al., 2024). Magnetization transfer imaging (MTI) detects myelin loss, complementing EP latency delays (Invernizzi et al., 2011). Magnetic resonance spectroscopy (MRS) identifies reduced N-acetylaspartate, signaling axonal loss, corresponding to absent EP amplitudes (Szynal et al., 2020). Medical physicists integrate these modalities with EPs, enhancing ML model accuracy (Koutsojannis & Chrysanthakopoulou, 2025).

Role of Medical Physicists in Electrophysiological Applications

Medical physicists are instrumental in electrophysiological applications, spanning ECG, EEG, SSEPs, and MEPs for diagnosing cardiac and neurological disorders (EFOMP, 1999; Medical physics, 2024). They design systems with microelectrode arrays, achieving 8–12 dB SNR improvements in EEG via WPD, enabling 41% more spike-wave complex detection in epilepsy monitoring (Chen et al., 2023; Beniczky et al., 2022). In neonatal seizure detection, AI models achieve 96.4% sensitivity with 8.3-second latency, surpassing clinical observation (Beniczky et al., 2022).

In Parkinson's disease, wearables monitor β-band (13–30 Hz) activity, achieving 94% burst detection versus 68% in clinical EEG, reducing DBS adjustment lags from weeks to 48 hours (Little et al., 2023; Espay et al., 2018). In cardiac monitoring, edge-AI detects arrhythmias with 94.2% accuracy, reducing false positives by 5–7% (Perez et al., 2019). The adoption of these technologies necessitates addressing ethical and regulatory complexities. Federated learning, while compliant with GDPR/HIPAA (Rieke et al., 2020), may inadvertently exclude underrepresented populations lacking digital infrastructure. Explainable AI (XAI) techniques like SHAP values (Lundberg et al., 2020) mitigate interpretability gaps but require clinician training to contextualize feature importance (e.g., SSEP latency contributing 42% to prognosis). Regulatory compliance is equally critical: the FDA's evolving 510(k) pathway for AI-driven devices now emphasizes post-market surveillance (Perez et al., 2019), necessitating continuous performance monitoring in real-world settings. Medical physicists must lead ethics committees to balance innovation with patient safety, as advocated by EFOMP (1999).

Quantum Sensors for High-Resolution EEG

Medical physicists are exploring nitrogen-vacancy (NV) diamond magnetometers for EEG, offering 10 pT/√Hz sensitivity versus 100 fT/√Hz in SQUID magnetometers (Barry et al., 2020). These sensors detect microtesla-scale neural magnetic fields, enabling high-resolution mapping of epileptiform activity. However, power consumption (10–100 mW) limits wearable applications.

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Ongoing research focuses on cryogenic-free designs and power-efficient electronics to achieve 1 mW consumption, supporting long-term monitoring (Hart et al., 2023).

Meta-Analysis: Methodology and Findings

Medical physicists' methodological interventions are exemplified by a meta-analysis evaluating EP-based ML models for SCI/MS prognosis (Koutsojannis & Chrysanthakopoulou, 2025). Five studies (n=586) were included, covering SCI (n=263) and MS (n=297), using SSEPs and MEPs to predict ASIA recovery, injury location, or EDSS progression. Models included Random Forests and deep learning, with accuracy ranging from 70.0% to 84.7% and AUC from 0.75 to 0.87 (Table 1). PubMed, Scopus, and Web of Science were searched (up to May 2025) using keywords like "evoked potentials," "machine learning," and "SCI/MS." Inclusion required ML models using EP metrics (latency, amplitude, time series) and performance metrics (accuracy, AUC). A random-effects model (DerSimonian-Laird) pooled estimates, with heterogeneity assessed via I^2 (56–62%). Sensitivity analyses excluded an animal study (Wang et al., 2017) for human-only robustness. Funnel plots and Egger's test (p=0.12–0.15) evaluated publication bias (Table 2). Pooled accuracy was 77.7% (95% CI 76.8–81.6%), with AUC 0.81 (95% CI 0.79–0.85). SSEP latency and MEP time series were universal predictors, with amplitude critical for SCI. Multimodal integration (SSEP-MRI) enhanced SCI predictions (Hoo et al., 2024). Sensitivity analysis (n=528) yielded 78.5% accuracy and AUC 0.81, confirming robustness. Moderate heterogeneity (I^2=56–62%) stemmed from EP types and ML methods (Koutsojannis & Chrysanthakopoulou, 2025) (Table 3).

Table 1. Study Characteristics (Adapted from Koutsojannis & Chrysanthakopoulou, 2025).

Study	Population	EP Type	ML Model	Outcome	Accuracy (%)	AUC
Chrysanthakopoulou et al. (2025)	MS, n=125	SSEP	Random Forest	EDSS progression	75.0 (70.2–79.8)	0.78 (0.73–0.83)
Chrysanthakopoulou et al. (2025)	SCI, n=123	SSEP	Random Forest	ASIA recovery	83.0 (78.4–87.6)	0.87 (0.83–0.91)
Yperman et al. (2020)	MS, n=223	MEP	Random Forest	EDSS progression	70.0 (64.8–75.2)	0.75 (0.70–0.80)
Cui et al. (2017)	SCI, n=32	SSEP	Random Forest	Injury location	84.7 (79.9–89.5)	0.85 (0.80–0.90)
Hoo et al (2024)	SCI, n=80	SSEP	Deep Learning	ASIA recovery	81.2 (76.0–86.4)	0.83 (0.79–0.87)

Table 2. ML Feature Importance in EP-Based Models.

Feature	Importance (Mean ± SD)	Application
SSEP Latency	0.42 ± 0.08	SCI/MS prognosis
MEP Time Series	0.35 ± 0.06	SCI/MS prognosis
SSEP Amplitude	0.18 ± 0.04	SCI prognosis
MRI Fractional Anisotropy	0.05 ± 0.02	SCI prognosis

Table 3. Heterogeneity Sources.

Source	I^2 (%)	Impact

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EP Type (SSEP vs. MEP)	58	Moderate
ML Model Type	62	High
Sample Size	56	Moderate

Impact on Clinical Outcomes

Medical physicists' innovations enhance clinical outcomes. Wearable EEG with WPD reduces indeterminate readings by 28% in epilepsy monitoring, detecting 41% more spike-wave complexes (Beniczky et al., 2022). Edge-AI enables earlier arrhythmia detection, reducing false positives by 5–7% (Perez et al., 2019). In SCI, EP-based ML predicts ASIA score improvements with 83% accuracy, guiding rehabilitation (Koutsojannis & Chrysanthakopoulou, 2025). In MS, models predict EDSS worsening with 70–76.5% accuracy, informing early interventions (Yperman et al., 2020). In Parkinson's, β-band monitoring reduces DBS adjustment lags to 48 hours (Little et al., 2023). Representative clinical scenarios are following for better understanding the above assumptions (Table 4).

Challenges and Future Directions

Challenges include limited recognition and resource constraints in low-income settings (Caruana et al., 2022). NV-diamond magnetometers' power consumption (10 mW) limits wearable EEG applications (Caruana et al., 2022). NV-diamond wagons consumption (10 mW) limits wearable EEG applications (Barry et al., 2020). Moderate heterogeneity in ML models (I^2=56%) and limited EP studies (n=6) constrain generalizability (Koutsojannis & Chrysanthakopoulou, 2025). Multicenter validation and standardized EP protocols are needed.

Table 4. Clinical Scenarios.

1	**Spinal Cord Injury**	A 35-year-old with a C6 incomplete injury undergoes SSEP assessment. An ML model predicts 83% likelihood of ASIA score improvement, guiding intensive physiotherapy and transcranial stimulation (Koutsojannis & Chrysanthakopoulou, 2025).
2	**Multiple Sclerosis**	A 42-year-old with relapsing-remitting MS shows prolonged SSEP latency. An ML model predicts 70% probability of EDSS worsening, prompting early ozanimod initiation (Yperman et al., 2020).
3	**Epilepsy**	A 27-year-old with focal epilepsy uses a wearable EEG, detecting 41% more spikes, refining surgical planning (Beniczky et al., 2022).
4	**Cardiac**	A 60-year-old with suspected atrial fibrillation uses a wearable ECG with edge-AI, achieving 94.2% accuracy, enabling timely anticoagulation (Perez et al., 2019).
5	**Stroke Monitoring**	A 55-year-old post-stroke patient uses wearable EEG with AI, detecting epileptiform activity (80% sensitivity), guiding levetiracetam therapy to prevent seizures (Hart et al., 2023).
6	**Atrial Fibrillation in Elderly**	An 83-year-old frail patient uses a wearable ECG for 72-hour monitoring, with edge-AI detecting paroxysmal atrial fibrillation (92% specificity), supporting apixaban initiation (Perez et al., 2019).
7	**Chronic Pain in SCI**	A 40-year-old with SCI undergoes SSEP testing. An ML model predicts 75% likelihood of neuropathic pain, recommending spinal cord stimulation (Jensen et al., 2020).

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Future research should prioritize federated learning for privacy-preserving data pooling and quantum-enabled sensors for higher resolution (Rieke et al., 2020; Barry et al., 2020). Integrating medical physicists into FDA/CE standardization committees will ensure regulatory-compliant devices, addressing barriers like power efficiency and validation gaps (FDA-NIH Biomarker Working Group, 2022). Prospective multicenter studies with larger cohorts (n=1000) will validate EP-based ML models, enhancing clinical applicability. Consequently MPs interventions expand on **workflow barriers** (e.g., clinician trust in AI, EHR integration), address potential biases in meta-analysis (e.g., small study effects, heterogeneity), and prioritize **regulatory pathways** (e.g., FDA/CE certification for quantum sensors).

Limitations

Several limitations must be acknowledged in these advancements. First, while AI models demonstrate high accuracy (e.g., 79.2% for SCI/MS prognosis), their performance may vary across patient populations due to heterogeneity in EP protocols and disease subtypes, as seen in the meta-analysis by Koutsojannis & Chrysanthakopoulou (2025) where I^2 values of 56-62% indicated moderate methodological diversity. Second, quantum sensors like NV-diamond magnetometers, despite their 10 pT/√Hz sensitivity, face practical barriers such as 10-100 mW power consumption (Barry et al., 2020), limiting wearable applications. Third, federated learning assumes consistent data quality across sites; variations in EP acquisition (e.g., stimulus intensity, electrode placement) could introduce bias, as noted in multicenter EEG studies (Beniczky et al., 2022). Addressing these challenges requires stricter standardization, exemplified by IEC 60601-2-47 guidelines for wearable devices (IEC, 2021).

Conclusion

Medical physicists and biophysicists are pivotal in advancing wearable electrophysiology and precision neurology, delivering innovations like 60% **motion artifact reduction**, 94.2% **accurate AI diagnostics**, and 79.2% **accurate EP-based prognostics** for SCI/MS. Their expertise in signal processing, AI, uncertainty quantification, and methodological research ensures reliable, regulatory-compliant technologies. By embedding these professionals in clinical and regulatory frameworks, healthcare systems can enhance diagnostic precision, optimize treatments, and improve patient outcomes, shaping the future of personalized medicine. Bridging disciplinary silos is paramount for translational success. The Movement Disorders Society's guidelines for wearable sensors (Little et al., 2023) demonstrate how standardized workflows can align engineers, clinicians, and physicists. Joint training initiatives, such as those for Monte Carlo dropout uncertainty quantification (Beniczky et al., 2022), foster shared understanding of AI limitations (e.g., σ >5% indicating low-confidence predictions). Embedding medical physicists in clinical teams, as seen in epilepsy monitoring units (Chen et al., 2023), ensures technologies meet bedside needs while adhering to IEC 60601-2-47 safety standards (IEC, 2021). This collaborative ethos, championed by IAEA (1996), will accelerate the transition from lab innovation to routine care.

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