AI Scribes: Physician Perceptions Range from 'Friend' to 'Threat'

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> The integration of artificial intelligence (AI) into clinical practice, particularly through AI scribes, presents a dichotomy in physician perception. While some clinicians view these tools as valuable adjuncts to patient care, others express apprehension regarding their broader implications for the medical profession.

KEY TAKEAWAYS

- The Pivot: AI tools are increasingly being developed for medical applications, including diagnostic support and data analysis.
- The Data: A machine learning tool, ActiTect, demonstrated an AUROC of 0.95 for REM sleep behavior disorder screening in a development cohort.1
- The Action: Clinicians should critically evaluate the evidence base for AI tools, focusing on generalizability and validation in diverse patient populations.

The development of machine learning models for diagnostic screening is advancing, with tools designed to identify specific medical conditions. For instance, ActiTect, an open-source machine learning pipeline, was developed to screen for rapid eye movement (REM) sleep behavior disorder (RBD) using standardized actigraphy. RBD is a prodromal marker for α-synucleinopathies, including Parkinson's disease and dementia with Lewy bodies.1

RBD is characterized by the enactment of dreams during REM sleep due to a loss of muscle atonia. This condition often precedes the motor symptoms of Parkinson's disease by several years, making early detection crucial for potential neuroprotective interventions. The prevalence of RBD in the general population is estimated to be between 0.5% and 1.2%, but it is significantly higher in patients with neurodegenerative disorders. Identifying individuals with RBD allows for closer monitoring and participation in research aimed at understanding and modifying the progression of α-synucleinopathies.

Study Design & Findings

ActiTect's pipeline includes robust preprocessing and automated sleep-wake detection to harmonize multi-device data and extract physiologically interpretable motion features. The model was developed using a cohort of 78 individuals, achieving strong discrimination with an AUROC of 0.95 under nested cross-validation.1 Generalization of the model was confirmed on a blinded local test set (n=31, AUROC=0.86) and two independent external cohorts (n=113, AUROC=0.84; n=57, AUROC=0.94).1 Robustness was further assessed through leave-one-dataset-out cross-validation across cohorts, which showed consistent performance (AUROC range=0.84-0.89).1 The predictive features remained reproducible

across datasets, supporting the deployment of the pooled multi-center pre-trained model.1

The preprocessing steps in ActiTect's pipeline are critical for standardizing data collected from various actigraphy devices, which often differ in sampling rates and sensor types. This harmonization ensures that the extracted motion features are comparable across different datasets, enhancing the model's generalizability. Automated sleep-wake detection algorithms within the pipeline accurately segment periods of sleep and wakefulness, allowing for the specific analysis of motion patterns during sleep, which is essential for RBD diagnosis. The extracted features include metrics related to movement intensity, frequency, and periodicity during REM sleep, which are indicative of dream enactment behaviors.
Another machine learning model was developed to detect sleep-disordered breathing in glaucoma patients, utilizing systemic and ophthalmic parameters.2 While the abstract for this study describes the same methodology and results as ActiTect, it highlights the application of machine learning in a different clinical context, suggesting the adaptability of such approaches across various medical specialties.2 Similarly, a systematic analysis for the Global Burden of Disease Study 2023 focused on the global burden of enteric infectious diseases and diarrhoeal diseases. The abstract for this study also describes the ActiTect methodology, indicating a potential misattribution or a broader discussion of machine learning applications in health data analysis.3

These studies illustrate the potential for AI and machine learning to contribute to early detection and understanding of disease burdens. The open-source nature of tools like ActiTect is intended to promote adoption, independent validation, and collaborative improvements, thereby advancing generalizable wearable-based detection methods.1

Limitations & Next Steps

While the ActiTect model demonstrated strong performance and generalizability across multiple cohorts, the initial development cohort consisted of 78 individuals.1 Further large-scale validation in diverse populations and clinical settings would strengthen the evidence for broader clinical implementation. The consistent performance across external cohorts is encouraging, but the specific characteristics of these cohorts (e.g., demographics, disease severity) would be important for a complete understanding of the model's applicability. The repeated abstract content across different PMIDs suggests a need for careful review of the distinct contributions of each publication, particularly when evaluating the specific clinical application of the machine learning models. The utility of AI scribes in the exam room, as implied by the topic, would require distinct research focusing on their impact on physician workflow, patient interaction, and documentation accuracy, which is not directly addressed by the provided research on diagnostic algorithms.

The relatively small size of the initial development cohort, while demonstrating strong internal validity, necessitates expansion to ensure the model's robustness across a wider spectrum of patient variability. Future research should aim to include cohorts with varying ethnic backgrounds, socioeconomic statuses, and comorbidities to assess the model's performance in real-world clinical scenarios. Additionally, the long-term predictive value of ActiTect in identifying individuals who will eventually develop overt α-synucleinopathies requires longitudinal studies. The integration of actigraphy data with other biomarkers, such as neuroimaging or cerebrospinal fluid analysis, could further enhance the diagnostic accuracy and prognostic capabilities of such machine learning models.

CLINICAL IMPLICATIONS

The enthusiasm for AI in medicine, particularly for tasks like diagnostic screening, is evident in the development of tools such as ActiTect. However, the current evidence base, exemplified by the repeated abstract content across different publications, underscores a critical need for precision in reporting and distinct validation for each specific clinical application. While an AUROC of 0.95 for RBD screening is impressive, it pertains to a diagnostic algorithm, not directly to the operational impact of an AI scribe in a consultation room. Clinicians should differentiate between AI as a diagnostic aid and AI as an administrative assistant; the former requires rigorous, disease-specific validation, while the latter demands scrutiny of its effects on patient-physician dynamics and documentation integrity.

The notion of an AI scribe as a 'friend in the exam room' versus a reason to 'sleep with one eye open' reflects a fundamental tension. If AI tools genuinely reduce administrative burden, allowing more direct patient engagement, they could enhance the physician experience. However, if they introduce new layers of complexity, data privacy concerns, or subtle shifts in accountability, their perceived benefit will diminish. The industry must move beyond demonstrating technical feasibility to proving tangible, positive impacts on clinical workflow and patient outcomes, supported by distinct, peer-reviewed evidence for each proposed application. For patients, the promise of AI lies in improved diagnostic accuracy and potentially more focused physician attention. Yet, the black-box nature of some AI algorithms and the potential for data misuse or errors remain concerns. Regulators and professional bodies will need to establish clear guidelines for the deployment and oversight of AI in clinical settings, ensuring that these technologies serve to augment, rather than replace, human judgment and empathy. The current research, while demonstrating the technical prowess of AI in

> specific diagnostic tasks, does not yet provide the comprehensive evidence needed to fully assess the broader implications of AI scribes on the clinical encounter.

EDITORIAL & AI STANDARDS

AI tools are used to structure and summarise evidence from peer-reviewed primary sources. Articles that carry a signed Editor's take have been read in full by William Lopes. The others are not individually read by an editor, so check the cited source before relying on a figure.

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