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PERSPECTIVE ARTICLE

Expertise in AI and clinical publishing exposes peer review gaps: A perspective

Ezra N. S. Lockhart*

Department of Marriage and Family Sciences, National University, San Diego, California, United States of America

Abstract

Artificial intelligence and machine learning are advancing rapidly in medical and mental health research, yet clinical publishing remains structurally unprepared to evaluate these technologies with the rigor they demand. Despite the rise of AI-driven models for suicide risk prediction and diagnostic assessment, editorial and peer review processes often lack the technical expertise required to assess methodological validity. Drawing on dual fluency in AI and clinical publishing, this perspective identifies a critical gap at the intersection of innovation and editorial oversight. This article reveals how editorial decisions in high-impact psychiatry journals have dismissed valid methodological concerns as "overly technical" and undermined independent scientific critique, drawing on two case studies: one involving a model that differentiates suicidal from non-suicidal self-harm, and another analyzing speech-based suicide risk assessment. These case studies serve as the foundation for a broader critique of editorial decision-making in clinical publishing, revealing persistent structural blind spots in evaluating AI-integrated research. To prevent the pre-mature adoption of flawed models in clinical care, this perspective proposes targeted reforms: recruiting technically proficient reviewers, mandating transparent methodological reporting, and protecting space for independent post-publication evaluation. Without such changes, the integrity of the field and the safety of patients remain at risk.

Keywords: Artificial intelligence; Peer review-research; Ethics-research; Editorial policies; Speech analysis

***Corresponding author:**
Ezra N. S. Lockhart
(elockhart@nu.edu)

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1. Introduction

The integration of artificial intelligence (AI) and machine learning (ML) into clinical research is no longer speculative.[1-10] From suicide risk detection to diagnostic classification, AI-driven tools are already shaping the future of mental healthcare.[11,12] Yet, while the promise of these technologies is real, so are the risks of their pre-mature adoption. The methodological complexity of AI systems demands careful scrutiny, but clinical publishing has not kept pace. Many journals lack both the technical infrastructure and editorial expertise required to evaluate these studies with the rigor they warrant.[13,14]

As a researcher-clinician with dual expertise in both AI development and clinical psychiatry, I have observed firsthand the challenges posed by this gap. Two critiques I submitted to high-impact psychiatry journals – one challenging an AI model differentiating suicidal from non-suicidal self-harm, the other critiquing a speech-based suicide risk detection system – were rejected not for inaccuracies in my evaluation, but for being "overly technical" or "lacking clinical relevance."[11-31] In one case, editorial processes allowed the original authors to pre-clear critiques, undermining the independence of peer review and suppressing substantive methodological discussion.[12]

These cases are not outliers. They reflect a deeper, systemic issue in how interdisciplinary research is handled in clinical publishing. Through these case studies, this perspective contributes to the ongoing discourse on peer review integrity by identifying structural editorial failures, analyzing their ethical and scientific implications, and proposing reforms to align publishing practices with the technical demands of AI-integrated mental health research.

2. The challenge of evaluating AI in clinical publishing

While transformative, AI and ML methods are not immune to significant flaws.[10,13,14] Unlike conventional clinical research methods (*e.g.,* randomized controlled trials, cohort studies, case-control studies, cross-sectional studies, case reports, and systematic reviews), AI-driven studies and studies using AI methods demand a nuanced understanding of data science principles, algorithmic transparency, model generalizability, and ethical implications.[19] Peer reviewers and editors in clinical journals, who may not be versed in the complexities of computational models, can unintentionally overlook or misinterpret issues that would be immediately evident to AI specialists.[13]

3. Case study 1: Methodological limitations of Haghish (2025)

This challenge was starkly evident when I submitted some correspondence to a high-impact psychiatry journal regarding a 2025 study by Haghish, titled "Differentiating Adolescent Suicidal and Nonsuicidal Self-Harm with Artificial Intelligence."[11] My critique focused on several key methodological concerns, including class imbalance, model interpretability, and generalizability, all essential to validate that AI models are both scientifically sound and clinically applicable.[15-29]

Class imbalance is a pervasive problem in supervised ML, especially in sensitive domains, such as adolescent self-harm, where suicidal attempts constitute a small minority of the dataset.[18,22,23,27,28] While Haghish employed synthetic oversampling techniques[18] (specifically the synthetic minority oversampling technique, SMOTE), these methods – although well-intentioned – carry inherent risks. Oversampling can inflate minority class representation artificially, leading to overfitting on synthetic samples that do not adequately represent real-world variation.[18,23] This undermines model robustness and compromises generalizability across unseen populations and clinical settings. In my correspondence, I wrote:

> *Class imbalance remains one of the most significant challenges in supervised machine learning, particularly in domains, such as adolescent self-harm, where suicide attempts represent a small portion of the dataset. The synthetic oversampling techniques employed, while well-intentioned, may risk overfitting and undermine generalizability.*

The clinical adoption of AI models hinges on transparent decision-making processes that clinicians can understand and trust. The original study lacked sufficient interpretability measures to explain how the model attributed importance to various features. I proposed integrating SHAP (SHapley Additive exPlanations) values to provide fine-grained, interpretable insights into feature contributions. SHAP values allow clinicians to see which factors most influenced the model's predictions in individual cases, facilitating informed clinical judgment and improving acceptance in high-stakes settings.[16,17] Specifically, I noted:

> *Integrating SHAP values could enhance the transparency of the model's feature attribution, making the system more interpretable to clinicians and better suited for high-stakes environments.*

Adolescents' behavioral and clinical profiles vary widely across different populations and healthcare contexts. The study's model was trained on a relatively homogeneous sample, limiting its applicability elsewhere. I suggested employing transfer learning techniques, which allow models to leverage knowledge from related datasets or tasks to improve performance on new, diverse cohorts.[24,26] Transfer learning offers a path to improve model adaptability and external validity, a key requirement for any AI tool intended for broad clinical use:

> *Transfer learning could offer a viable path to improve generalizability, particularly across diverse clinical settings or populations not represented in the original training data.*

The letter was ultimately rejected, with editorial feedback stating that these methodological concerns were "outside the journal's thematic scope."[13,14] While editorial discretion is understandable, this dismissal raises deeper issues about how clinical journals vet AI-driven research. By sidelining fundamental questions about model rigor and applicability, the editorial board risks perpetuating the publication of AI studies that lack sufficient scientific and ethical scrutiny.[13,14,19-21] This episode exemplifies a recurring problem: clinical journals often lack the necessary expertise, infrastructure, or review frameworks to rigorously evaluate the technical complexities and ethical dimensions of AI and ML in mental health research. Without such mechanisms, flawed models with serious real-world consequences may be accepted uncritically.[13,14,19-21]

4. Case study 2: Methodological oversights of Ding *et al*. (2025)

The systemic editorial failures seen in the Haghish case were not isolated. A study by Ding *et al.*,[12] titled "Speech-Based Suicide Risk Recognition for Crisis Intervention Hotlines Using Explainable Multi-task Learning," innovatively applies multi-task learning (MTL) and explainable AI (XAI) to speech-based suicide risk detection in crisis hotline calls. Although innovative, several methodological choices warrant further scrutiny, particularly regarding speech pre-processing, feature extraction, model architecture, and multimodal integration.[28]

A major concern is the removal of silences longer than 1 s from speech segments. Silences carry important emotional weight in high-stress contexts, indicating hesitation or distress, and their exclusion could lead to loss of critical psychological signals.[27] As stated in my letter:

> *Silence in speech, particularly during high-stress crisis calls, can carry emotional weight; its removal may obscure indicators of hesitation, distress, or emotional regulation.*[25-27]

Excluding these silences risks discarding valuable psychological signals that are integral to accurately assessing caller emotional state.[25,27] Transformer models with self-attention mechanisms (*e.g.*, Wav2Vec 2.0) are better suited to capture such long-range dependencies without omitting silent intervals.[24,28]

The authors also utilized a fixed 5-s segmentation window for feature extraction, which may be too rigid to capture the inherently non-linear and rapidly fluctuating emotional content in crisis speech.[28,29] I argued:

> *The use of fixed 5-s segmentation windows may prevent the model from capturing the dynamic fluctuations typical in crisis speech patterns.*

More flexible temporal modeling approaches, such as variable-length sequences handled by transformers with multi-head attention, or techniques, such as sliding windows and dynamic time warping, could better capture these rapid emotional transitions.[24-26]

Regarding feature extraction, the research team extracted 178 paralinguistic features but did not clearly explain their prioritization or integration within the model. Feature interactions in speech emotion recognition are complex, non-linear, and context-dependent. I highlighted that:

> *These technical issues have direct implications for suicide risk classification and cannot be dismissed as merely academic.*[13-15]

Advanced feature selection techniques, such as SHAP-based approaches or quantum-behaved particle swarm optimization (QPSO), have shown promise in refining discriminative feature sets to improve performance and interpretability, suggesting avenues for methodological improvement.[17,23,25]

Regarding model architecture, while Bidirectional Long Short-Term Memory (Bi-LSTMs) capture some temporal dependencies, they have inherent limitations in modeling long-range context.[24,26] Transformer-based architectures outperform Bi-LSTMs by leveraging multi-head attention and enabling more interpretable focus on critical speech segments.[24,26] I emphasized:

> *"The limitations of Bi-LSTM architectures in capturing long-range emotional dependencies" diminish the model's ability to detect subtle emotional variations over extended speech segments.*

Recent pre-trained transformer speech models (*e.g.*, HuBERT) further demonstrate robustness and efficiency in real-world noisy environments, making them preferable for this application.[28]

Finally, the study's exclusive reliance on speech features overlooks the benefits of multimodal integration. Combining speech with textual transcriptions or physiological data has been shown to improve emotion detection accuracy and model robustness, especially in complex, high-stakes environments, such as crisis hotlines.[26,29,30] Despite the substantive and clinically relevant nature of these critiques, the editorial board rejected the letter as "overly technical" and "lacking clinical relevance." This dismissal highlights a systemic editorial issue wherein rigorous methodological critique of AI models is marginalized, risking the publication of flawed models with potential real-world harms.[19-21,30,31]

5. Editorial gatekeeping and conflicts of interest

The methodological shortcomings outlined in both case studies are not anomalous oversights but symptomatic of deeper structural failures in editorial practices governing AI in mental health research. A recurring theme in both rejections was that the letters were "overly technical" or "outside scope" – feedback suggesting that editorial boards often defer scientific vetting to original authors, a process colloquially referred to as *pre-clearance*. While this practice may be intended to streamline correspondence handling, it effectively allows original authors to veto external critique, compromising the neutrality and independence of peer review.[32-38]

This gatekeeping is further exacerbated by a systemic lack of technical and ethical expertise among clinical journal editors to assess AI-related submissions. As ML models become more complex and deeply integrated into healthcare, editorial boards must be equipped to evaluate not only clinical relevance but also algorithmic validity, interpretability, and fairness.[30,31] Without such expertise, editorial decisions may inadvertently privilege esthetic novelty or positive results over scientific rigor and replicability.

In many journals, the peer review process itself remains opaque and insufficiently diverse, further contributing to biased publication outcomes. Studies show that increasing gender and international diversity among reviewers correlates with fairer evaluations and higher-quality editorial outcomes.[33-35] Yet, even in journals that acknowledge these disparities, few have adopted concrete reforms, such as blind review, reviewer training in AI ethics, or structured checklists for evaluating ML studies.[19,30,39-45]

As generative AI continues to scale across clinical domains, scholars have increasingly called for the integration of *embedded ethics* into the development, evaluation, and dissemination of medical AI research.[39-45] This approach demands that ethical concerns – such as algorithmic bias, safety, transparency, and explainability – be addressed from the outset, not appended *post hoc*. In this model, ethics is not a checkpoint at the end of the pipeline but a structural element of rigorous scientific inquiry.

Despite these calls, the editorial handling of the critiques toward the works of Haghish[11] and Ding *et al.*[12] suggests that present publishing norms fall short of AI-driven studies and studies using AI methods. The absence of substantive engagement with these challenges implies that many journals remain ill-equipped – or unwilling – to enforce ethical scrutiny as part of peer review. Without meaningful reform in areas, such as editorial independence, reviewer training, and conflict-of-interest transparency, flawed AI models may continue to bypass critical evaluation and enter the clinical literature unchallenged.

This failure is not merely procedural. It raises foundational questions about epistemic authority in clinical AI:

- Who determines what constitutes valid evidence?
- Who is accountable when predictive models reinforce structural bias or contribute to diagnostic error?

In the absence of systemic safeguards, the pre-mature adoption of under-evaluated AI tools threatens not just the integrity of the scientific record but the safety and equity of patient care.[30,31,39,40]

6. Comparative analysis across cases

The rejection of substantive methodological critiques in both the Haghish[11] and Ding *et al.*[12] case studies reveals consistent patterns of editorial gatekeeping, technical exclusion, and ethical under-evaluation. While the studies addressed different domains (*i.e.*, text-based versus speech-based suicide prediction), the nature of the overlooked issues and the editorial rationale for rejection were strikingly similar. These cases demonstrate that systemic editorial deficiencies can transcend methodological domain, modality, and even discipline.

Table 1 summarizes the critical methodological concerns raised in each case, mapping them to potential clinical consequences and corresponding editorial responses. This side-by-side view makes visible the shared vulnerabilities in AI health research publication and underscores the urgency for reform in peer review protocols.

Figure 1 shows a conceptual model depicting the multi-layered nature of editorial gatekeeping and its consequences. Critique pre-clearance, limited AI literacy, and narrow definitions of clinical relevance combine to create significant obstacles. Together, these factors build barriers that obstruct scientific accountability.

Together, these cases illustrate a systemic breakdown in editorial accountability. When valid methodological critiques are filtered out by opaque editorial practices or vetoed by original authors, the epistemic integrity of the scientific record is compromised. Moreover, the publication of inadequately vetted AI models has serious clinical and ethical implications.

7. Limitations

In discussing the constraints within editorial decision-making, I recognize several key factors that shape how scholarly work and professional discourse are disseminated. Journals operate within specific editorial frameworks that dictate what content is selected for publication. These policies may prioritize particular research methodologies or thematic focuses, inadvertently shaping which perspectives enter the broader academic conversation.[20,21,32-38]

The peer-review process, while intended to ensure rigor and credibility, is subject to variability in reviewer expertise,

Table 1. Summary of critiques and editorial responses across two case studies

Dimension	Case study 1 (Haghish, 2025)[11]	Case study 2 (Ding *et al.*, 2025)[12]
Data imbalance	Overreliance on SMOTE without evaluation of generalizability.	Not applicable.
Model interpretability	Lacked SHAP-based or interpretable mechanisms.	Feature attribution unclear; 178 features used without ranking.
Generalizability	Single-site data; no external validation or transfer learning.	No discussion of generalizability beyond one speech corpus.
Temporal modeling	Not applicable.	Fixed 5-s windows insufficient for dynamic emotional variance.
Silence removal	Not applicable.	Silences removed, obscuring emotional/psychological cues.
Model architecture	Not discussed.	Bi-LSTM used despite limitation; transformers not explored.
Multimodal design	Not applicable.	Speech-only; no integration of text, physiology, or behavioral context.
Proposed improvement	SHAP, transfer learning, balanced evaluation.	Transformer models, QPSO, SHAP, multimodal fusion.
Potential consequence	Misclassification in adolescent self-harm; clinical misapplication.	Missed suicide risk signals; failure in real-world crisis detection.
Editorial justification	"Outside scope."	"Overly technical."

Abbreviations: Bi-LSTM: Bidirectional Long Short-Term Memory; QPSO: Quantum-behaved particle swarm optimization; SHAP: SHapley Additive exPlanations; SMOTE: Synthetic minority over-sampling technique.

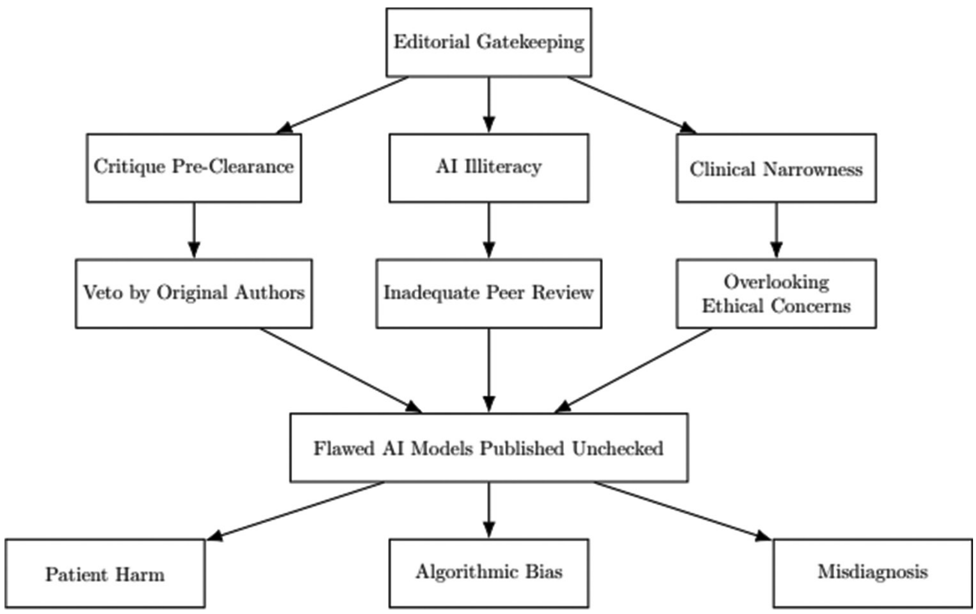

Figure 1. Editorial gatekeeping in artificial intelligence health research

implicit biases, and institutional priorities that may limit the diversity of published viewpoints.[32-38] Because of space limitations and journal formatting constraints, the scope of arguments permissible within letters to the editor is frequently restricted; moreover, although such letters serve as a platform for academic discourse, their acceptance remains contingent upon editorial discretion and alignment with the journal's thematic priorities.[32,37] The visibility of alternative frameworks within scholarly publishing is influenced by citation networks, funding availability, and institutional affiliations, affecting the accessibility of critical perspectives outside dominant paradigms.[19,32-38]

Journals, including digital-only platforms, must often balance the volume of valid commentaries they receive against practical considerations, such as editorial resources and thematic coherence, making it unrealistic to publish all submissions regardless of their merit.[32] Furthermore, the sensitive nature of mental health data imposes significant privacy constraints that restrict the open sharing of patient-level information. Ethical and legal obligations to protect participant confidentiality limit access to raw datasets, which complicates reproducibility and external validation efforts – challenges well documented in AI healthcare research.[39-43] These factors underscore the need for adaptive publication policies and innovative data governance frameworks that balance scientific transparency with the ethical imperatives unique to this field.

8. Calls for reform: Elevating the standards of peer review

To ensure the safe and effective integration of AI into clinical practice, scientific publishing – especially in clinical journals – must reform its approach to reviewing AI and ML research. To that end, the following recommendations are proposed:

- *Expert reviewers for AI methodologies:* Journals should engage data science and AI experts to identify technical flaws and verify the reproducibility, transparency, and robustness of the models.
- *Transparent model evaluation:* Manuscripts must provide explicit details regarding model training, data handling, and algorithm performance while addressing issues, such as class imbalance, bias, and interpretability.
- *Encouraging open data and code:* To facilitate reproducibility, journals should promote the sharing of data and code, enabling independent verification and improvement of AI models.
- *Dedicated spaces for AI methodological critiques:* Creating sections devoted to methodological discussion can encourage healthy academic discourse and improve the quality of published research.
- *Ethical and clinical considerations:* All AI-driven studies should include mandatory sections on ethics—analyzing informed consent, privacy, and potential harm—to ensure safe and responsible applications in clinical settings.

9. Final thoughts: Upholding scientific rigor and ethical standards

As AI continues to permeate healthcare, the imperative for rigorous, methodologically sound research grows ever more urgent. Inaccurate or insufficiently validated AI models risk fatal errors—misclassifying suicide risk, withholding necessary care, or prompting harmful interventions. These are not abstract concerns; they are life-or-death consequences of editorial decisions made today.

Clinical journals serve as critical gatekeepers of scientific integrity, and they must adapt to the challenges posed by the complexity and novelty of AI-driven methodologies. Only through independent, transparent, and technically informed peer review can the scientific community ensure that AI tools are deployed ethically, effectively, and safely in clinical settings. By embracing robust methodological critique rather than dismissing it as "overly technical," journals protect not only the rigor of science but also the well-being of vulnerable patients.

Looking ahead, future research should explore interdisciplinary innovations to enhance the robustness, interpretability, and clinical utility of AI models in mental and medical health. Emerging computational frameworks[46-49] – such as those based on circular bipolar complex intuitionistic fuzzy linguistic information, Frank power aggregation operators, and MABAC models – have demonstrated success in fields, such as renewable energy analysis and wireless communications. In addition, approaches employing neuro-fuzzy, complex propositional picture fuzzy Sugeno–Weber power aggregation and fractal mathematics, including superior Mandelbrot sets, offer promising avenues for managing uncertainty and improving model transparency.[50-57] While these advanced techniques have yet to be widely applied in mental or medical health AI, their adaptation holds potential to address critical methodological challenges, including class imbalance, model interpretability, and generalizability. Integrating such innovations could complement editorial reforms, pushing the field toward more reliable, ethical, and clinically impactful AI and ML applications.

This perspective highlights systemic failures in editorial oversight and offers concrete recommendations to reform peer review processes – reforms essential to maintaining trust in both AI research and its real-world applications. Without such change, the promise of AI risks becoming overshadowed by preventable harm and eroded confidence. Addressing these challenges is not optional; it is a critical responsibility that the scientific community and clinical publishers must urgently embrace to protect both patients and the integrity of mental health research.

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