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EDITORIAL

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Digitally and intelligently empowered perioperative care: a shift toward perioperative human-centered AI

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Digital health technologies and artificial intelligence (AI) are profoundly transforming perioperative medicine. From preoperative risk stratification and intraoperative clinical decision support to postoperative remote monitoring, AI applications have become increasingly integrated across the perioperative continuum of care [1–3]. However, an increasingly evident translational gap persists: many high-precision technologies demonstrate excellent performance in data-driven studies, yet their adoption and impact in real-world clinical practice remain substantially below expectations [4]. The advancement of perioperative intelligence should not merely pursue the accumulation of AI technologies but should also focus on developing human-centered AI. Human-centered perioperative AI has the potential to alleviate clinicians' cognitive load, augment rather than replace clinical judgment, and better accommodate the inherent complexity of perioperative care [5–7]. This editorial highlights the role of digitally and intelligently empowered perioperative medicine and calls for human-centered AI, integrating insights from recent progress in the field and relevant articles published in Anesthesiology and Perioperative Science.

1 Digital and AI-driven perioperative care: toward anticipatory care

AI algorithms trained on large-scale datasets can identify patterns preceding perioperative adverse events such as intraoperative hypotension, blood product requirements, postoperative ICU admission, mortality, and surgical site infections [4, 8–12]. This enables early prediction, providing healthcare teams with valuable time for intervention. From a patient safety perspective, this represents a significant advancement: clinicians are no longer limited to reactive responses but can move toward prophylactic care, thereby reducing delays in the recognition and management of adverse events.

Algorithmic approaches have evolved from conventional statistical modeling to encompass machine learning, deep learning, and multimodal fusion, driving a continuous enhancement in prediction performance. Nevertheless, issues related to algorithmic transparency, interpretability, clinical validation, and potential over-reliance on machine recommendations remain unresolved [1, 13]. First, most studies are based on retrospective, single-center datasets and lack prospective,

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multicenter validation, raising concerns regarding their generalizability and real-world applicability [4, 12]. Second, many models remain correlational rather than causal, identifying associations but rarely elucidating truly modifiable contributors of outcomes. Third, predictive performance may deteriorate over time because of data drift and concept drift, potentially compromising model reliability in evolving clinical environments. Moreover, most AI research teams have not yet reported the clinical deployment of their published models. Finally, AI-based tools are unlikely to improve patient care unless they are effectively integrated into existing electronic health record systems and clinical workflows.

Beyond risk prediction and clinical decision support, AI-based closed-loop anesthesia systems is expected to improve responsiveness and reduce the cognitive workload of anesthesiologists. These technologies have the potential to automate repetitive tasks, including anesthetic titration and administrative workflows, thereby improving efficiency and reducing clinician workload [14]. Although AI-driven closed-loop anesthesia systems can offer stability, they cannot replace human dimensions or competencies such as ethical responsibility, clinical intuition, situational awareness, and accountability [15]. Furthermore, generative AI, specifically large language models (LLMs), hold potential for facilitate perioperative intelligent anesthesia management [10]. Owing to their reasoning capabilities, multimodal information processing, and long-context understanding, LLMs can support a wide range of perioperative functions, from risk prediction and clinical decision support to precision interventions and workflow optimization [16].

Despite the continuous development of AI in the medical field, rigorous patient-centered empirical evidence demonstrating its clinical benefits remains scarce. This highlights the need for prospective randomized clinical trials to study the effects of human-AI collaboration before clinical adoption [17].

Future research should define a clear pathway for clinical implementation from the earliest stages of development, foster close collaboration between clinicians and AI engineers through co-design approaches, and place greater emphasis on implementation science evaluations of real-world deployment rather than pursuing technical complexity for its own sake [18–20]. Intelligent tools must be rigorously validated across diverse surgical populations and clinical scenarios to ensure the fairness and reliability. Crucially, these technologies should augment, rather than replace, the clinical judgment of experienced teams while remaining human-centered. Nevertheless, the trajectory is clear: AI is transforming perioperative care from an intuition-based decision model to a data-driven one, thereby enhancing safety, consistency, and clinical outcomes.

2 High-quality data-driven development of perioperative intelligence

Perioperative intelligence generates massive multi-modal data characterized by the classical "4Vs": volume, variety, velocity, and value, that is multi-dimensional and heterogeneous [1–3]. However, compared with many databases in the critical care field (e.g. MIMIC-IV, eICU database), high-quality perioperative databases and cohorts are still scarce [1–3]. Notably, researchers from China are also striving to build high-quality perioperative patient-specific cohorts, such as China surgery and anesthesia cohort (CSAC), PeRiOperative sTress risk assEssment and Clinical decision cohorT (PROTECT) [21, 22]. Future research should strengthen the collection and processing of perioperative information, including preoperative and intraoperative time-series data, as well as postoperative follow-up outcomes. Promoting development of perioperative intelligence through real-world data requires robust, high-quality multicenter datasets, effective data sharing frameworks, and standardized data formats.

3 The shift toward perioperative human-centered AI

With the rapid evolution of AI, future research in intelligent perioperative medicine should be guided by the World Health Organization (WHO)'s guidance *Ethics and Governance of Artificial Intelligence for Health* [23]. This guideline provides a comprehensive framework for the ethical application of artificial intelligence technology in healthcare, centered around six consensus principles: protecting human autonomy; promoting human well-being, safety, and public interest; ensuring transparency, explainability, and intelligibility; fostering responsibility and accountability; ensuring inclusiveness and equity; and promoting responsive and sustainable AI systems. The WHO guidance provides a crucial framework for the development of AI in the perioperative field. For AI aimed at improving patients' perioperative safety, these principles are not merely aspirational ideals but practical requirements for implementation. AI should serve as a tool to facilitate the clinical decision-making, the human-centered approach will not only improve clinical outcomes but also reframe the ultimate goal of healthcare delivery within the complex perioperative environment.

At the same time, it must be clearly recognized that the actual effectiveness of AI depends not only on its technical performance but also on the quality of human-AI interaction and the appropriate interpretation of its outputs [24]. The probabilistic nature of AI

outputs, limited interpretability, adaptive behavior, risk of misclassification, and capacity to generate large volumes of data may introduce unique human factors challenges in perioperative care. Drawing on human factors analysis, the following seven considerations during the research process can help build human-centered AI: defining intended users and excluded populations in advance, designing outputs that are clinically trustworthy and interpretable, prioritizing integration into clinical workflows, providing training to prevent skill degradation, ensuring safe backup pathways, monitoring real-world deployment scenarios, and clearly communicating updates. Incorporating AI-specific human factors considerations into routine regulatory and health technology assessment processes can reduce preventable harm while supporting innovation.

Future progress will depend on strong interdisciplinary collaboration among clinicians, computer scientists, data scientists, and software engineers. Such sustained partnerships can enhance data quality, improve model robustness, and facilitate the successful translation of AI into clinical practice. Educational reform is equally critical. Future anesthesiologists must be proficient not only in physiology and pharmacology but also in data literacy, algorithmic reasoning, and human-AI collaboration. Societal acceptance of AI-assisted perioperative care depends on transparency, accountability, and demonstrable patient benefit [15]. By thoughtfully integrating AI into clinical practice, the medical community can deepen scientific understanding, enhance patient care, and reshape the future landscape of anesthesia and perioperative medicine.

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Authors' contributions
RZ and SA conceived the content of this manuscript, and they wrote the original draft. ZYL, XRP, YQW, KL, GC, XCH and TZ reviewed and edited the draft. All the authors have read and approved the manuscript.

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Declarations

Ethics approval and consent to participate
Not applicable.

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