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REVIEW

AI-enhanced simulation platforms for ultrasound-guided regional anesthesia: bridging theoretical knowledge and clinical proficiency

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Abstract

This article looks at the development of artificial intelligence (AI)-enhanced ultrasound-guided regional anesthesia simulation platforms and their use in medical education. As the complexity of regional anesthesia procedures grows, traditional teaching methods fail to address the clinical urgency of reducing preventable complications, such as inadvertent vascular puncture (reported incidence: 4.1–6.8%) and incomplete nerve blockade. These complications not only compromise patient safety, but also highlight a critical "expertise gap" between theoretical knowledge and practical execution. These AI-enabled simulation platforms can provide more realistic clinical scenarios, helping medical students and residents translate theoretical knowledge into practical skills. This review provides a comprehensive analysis of the current technologies, educational outcomes, and their role in enhancing clinical competency in regional anesthesia.

Keywords

AI-enhanced; Ultrasound-guided; Regional anesthesia; Simulation platforms; Medical education; Deep learning; Clinical competency; Adaptive learning

1. Background

Ultrasound-guided regional anesthesia (UGRA) has revolutionized perioperative care by enabling real-time visualization of nerves and vasculature, reducing complication rates compared with landmark-based techniques. Despite its clinical superiority, mastery of UGRA requires many supervised procedures—a threshold unattainable for many trainees due to limited clinical opportunities [1, 2]. Traditional education models, reliant on didactic lectures and passive observation, fail to address the cognitive demands of integrating ultrasound interpretation with needle manipulation, leading to a high error rate in anatomical identification among novices. Effectively training healthcare providers in this technique remains a significant challenge. Conventional UGRA instruction remains constrained by three critical limitations: (1) Absence of objective, real-time performance metrics during phantom practice [3], (2) Inability to simulate rare anatomical variations representing clinical cases [4], and (3) Fixed training protocols that fail to adapt to individual learning curves—a factor contributing to trainees requiring extended clinical supervision [5]. These systemic shortcomings directly correlate with preventable complications, including inadvertent vascular puncture (4.1–6.8% incidence) and incomplete nerve blockade [2, 6].

The integration of artificial intelligence (AI) into medical simulation offers transformative solutions to these challenges [7–10]. Contemporary AI-enhanced platforms combine three key technological advances: (1) Deep learning-driven image interpretation: In a retrospective validation study, convolutional neural networks (CNNs) were reported to achieve 92.7% accuracy in differentiating nerve fascicles from artifact signals in real-time ultrasound streams, surpassing novice practitioner performance [11]; (2) Physics-engine reinforced learning models simulating tissue deformation patterns across many anatomical variants [2], and (3) Adaptive difficulty algorithms that dynamically adjust simulation complexity based on trainee multimodal inputs (eye-gaze tracking, probe pressure sensors, and hand kinematics) [12–14]. These platforms utilize smart algorithms to analyze performance data and provide immediate feedback, improving the learning process. AI's ability to identify anatomical structures during ultrasound scans has been tested in studies [15]. Several pilot studies and small cohort comparisons suggest that AI systems can improve the accuracy of anatomical identification and overall practitioner performance, especially for those with less experience [16, 17]. This indicates that AI not only helps in learning technical skills, but also builds confidence and self-efficacy in trainees [11, 18]. This paradigm shift addresses the critical need for deliberate practice environments that bridge the "expertise gap" between theoretical knowledge and psychomotor execution.

To provide a methodologically rigorous foundation for this review, a systematic literature search was conducted across PubMed, Institute of Electrical and Electronics Engineers (IEEE) Xplore, and Google Scholar for relevant publications from 2010 to 2024. The search strategy employed a combination of keywords and Boolean operators, such as (“artificial intelligence” OR “deep learning”) AND (“ultrasound-guided regional anesthesia” OR “UGRA”) AND (“simulation” OR “medical education”), and was restricted to English-language articles. Guided by the Patient/Population, Intervention, Comparison, Outcome (PICO) framework, this review examines how AI-enhanced UGRA simulation platforms are redefining education through four key dimensions: the technological foundations of current platforms; validation studies comparing AI-assisted *vs.* traditional training outcomes; implementation challenges in curriculum integration; and future directions for personalized competency development. The synthesis of this literature reveals that AI’s data-driven approach can identify individual learning patterns and pitfalls, allowing for customized instruction that improves training quality and helps ensure practitioners can perform UGRA safely and effectively [18].

2. Methods

2.1 Search strategy

The study selection process is summarized in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram (see Fig. 1).

A comprehensive literature search was performed across PubMed, IEEE Xplore, and Google Scholar for articles published between 01 January 2010 and 30 June 2024. The search utilized a combination of keywords and Boolean operators (see Table 1).

2.2 Study selection and eligibility criteria

Studies were included if they met the following PICOS criteria: Population (P): Medical trainees (students, residents) or practicing anesthesiologists involved in UGRA training. Intervention (I): Use of AI-enhanced simulation platforms for UGRA training. Comparison (C): Traditional training methods (*e.g.*, didactic lectures, phantom models, and non-AI simulation). Outcomes (O): Measures of skill acquisition, procedural accuracy, error rates, learning curves, confidence levels, or clinical performance. Study Design (S): We included randomized controlled trials (RCTs), non-randomized comparative studies, cohort studies, case-control studies, and validation studies. Exclusion criteria included: Editorials, conference abstracts without full text, non-English language publications, and studies not involving AI or simulation.

PICOS Criteria: Clearly defined as follows: Population: Medical trainees and anesthesiologists; Intervention:

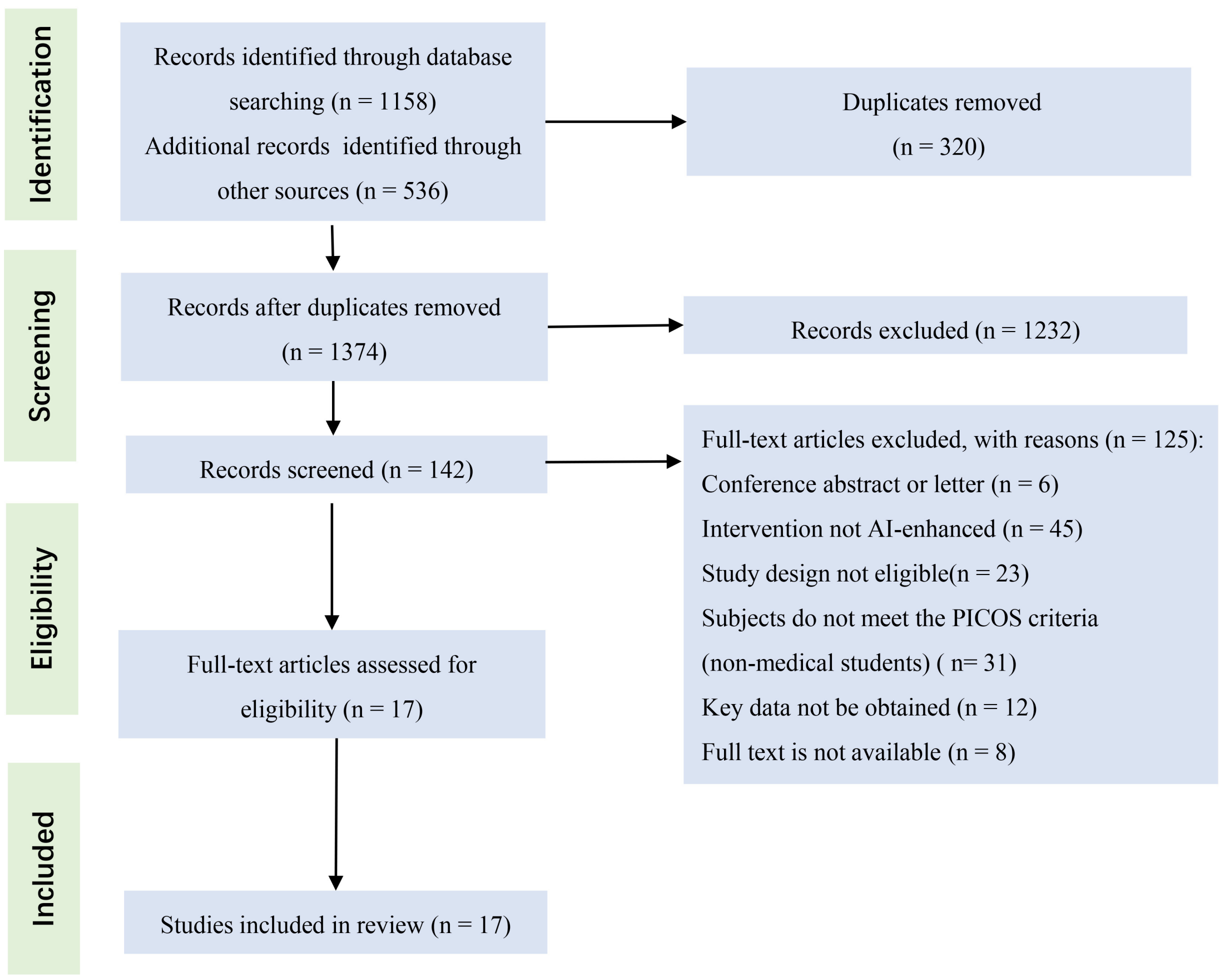

FIGURE 1. PRISMA flow diagram. Illustrating the study selection process for the systematic review on AI-enhanced UGRA simulation platforms. AI: artificial intelligence; PICOS: Patient/Population, Intervention, Comparison, Outcome, Study Design.

TABLE 1. Detailed search strategy by database.

Database	Search Query
PubMed	(“artificial intelligence”[Mesh] OR “deep learning”[Mesh] OR “machine learning”[Mesh]) AND (“ultrasound-guided regional anesthesia” OR “UGRA”) AND (“simulation”[Mesh] OR “education”[Mesh] OR “training”[Mesh])
IEEE Xplore	(“Artificial Intelligence” OR “Deep Learning”) AND (“Ultrasound-Guided Regional Anesthesia” OR “UGRA”) AND (“Simulation” OR “Medical Education”)
Google Scholar	artificial intelligence OR deep learning AND ultrasound-guided regional anesthesia AND simulation OR medical education

UGRA: Ultrasound-guided regional anesthesia; IEEE: Institute of Electrical and Electronics Engineers; Mesh: Medical Subject Headings.

AI-enhanced UGRA simulation platforms; Comparison: Traditional training methods; Outcomes: Skill acquisition, error rates, procedural success, and confidence; Study Designs: RCTs, cohort studies, validation studies, and comparative trials; Study Selection Process: Inclusion and exclusion criteria, screening process, and data extraction methods. A narrative synthesis was performed due to heterogeneity in outcomes and study designs.

3. AI-enhanced UGRA simulation platforms: a multi-dimensional analysis

This review examines how AI-enhanced UGRA simulation platforms are redefining regional anesthesia education through four key dimensions: Technological foundations of current platforms; Validation studies comparing AI-assisted *vs.* traditional training outcomes; Implementation challenges in curriculum integration; Future directions for personalized competency development.

3.1 Technological foundations of current platforms

3.1.1 The role of machine learning algorithms in image recognition

Machine learning (ML) algorithms now play a pivotal role in medical image recognition [19, 20], especially in UGRA. CNNs are particularly important for accurately identifying anatomical structures, which is crucial for successful medical procedures [21, 22]. CNNs can automatically learn spatial hierarchies from images, allowing them to capture the unique characteristics of ultrasound images, which vary significantly in echogenicity and tissue density. In UGRA, CNNs help recognize anatomical features with high accuracy [22, 23]. In controlled validation studies, AI systems have demonstrated the capability to assist anesthesiologists in identifying these features, with reported success rates as high as 99.7% in specific, well-defined tasks [24], primarily by reducing identification errors and improving interpretative confidence for less experienced practitioners [25, 26]. However, these findings primarily stem from experimental settings and require confirmation in broader clinical trials [16]. This is especially helpful for practitioners who are less experienced in anatomical identification, as the algorithms provide real-time feedback and highlight critical structures. The application of ML not only improves the precision of image interpretation but also reduces the risk of complications, thereby enhancing overall patient safety [27].

The working process of CNNs involves several stages. First, in the convolutional layer, filters convolve with the input ultrasound image to generate feature maps that emphasize various aspects, such as shape and texture. For example, these feature maps can learn to highlight sonographic features, such as the anechoic, rounded shape of blood vessels or the hyperechoic, fascicular (“honeycomb”) structure of peripheral nerves, which are critical for accurate anatomical identification in UGRA [28–30]. Then, pooling layers like max-pooling are used to reduce the dimensionality of the feature maps, further optimizing the model’s performance. Beyond ultrasound, ML is also changing other medical imaging methods, including X-rays and Magnetic Resonance Imaging (MRI) [31]. CNNs have shown great potential in automating the detection of abnormalities, making the diagnostic process more efficient. For instance, a CNN was used to classify bladder tumors in cystoscopic images [32, 33], achieving accuracy levels that sometimes exceed human capabilities, especially when trained on large datasets [34]. This shows that the integration of ML in image recognition allows for continuous learning and adaptation, which is essential in a field where anatomical variations can significantly impact procedural outcomes [35]. Moreover, the effectiveness of these algorithms is enhanced by their ability to learn from feedback. For instance, AI systems can adjust their predictions based on clinician input, refining their accuracy over time. This dynamic learning process is critical in medical settings where the stakes are high and the margin for error is low. Additionally, the use of AI in image recognition can facilitate personalized medicine by providing tailored diagnostic insights based on individual patient data, thus fostering a more patient-centered approach to healthcare [36].

3.1.2 AI-driven skill acquisition: from real-time feedback to learning optimization

Deep learning (DL) models, particularly those employing CNNs and reinforcement learning frameworks, have revolutionized skill acquisition in UGRA training by enabling dynamic, personalized feedback mechanisms. These models analyze procedural performance in real time, offering immediate corrections for needle trajectory deviations or suboptimal probe positioning (*e.g.*, "Your needle angle exceeds 15° from the target nerve bundle"). Preliminary evidence from simulation-based cohort studies indicates that such real-time feedback may accelerate skill mastery and reshape learning curves by targeting individual weaknesses [37–39]. The adaptive nature of DL models further optimizes long-term skill retention. By tracking performance metrics over time (*e.g.*, anatomical identification accuracy, and procedural duration), AI systems generate tailored training modules that progressively increase in complexity. This approach mirrors the "zone of proximal development" theory in educational psychology, ensuring trainees remain challenged without becoming overwhelmed. Notably, AI's ability to simulate rare clinical scenarios (*e.g.*, aberrant vascular anatomy) addresses a critical gap in conventional training, where exposure to such cases is often limited.

3.1.3 Translating AI innovations to clinical challenges in UGRA

The ultimate value of these technological foundations lies in their ability to address persistent clinical challenges in UGRA. For instance, the technical advancements in AI-driven simulation platforms directly address persistent clinical challenges in UGRA [9, 15, 40, 41]. A prime example is the difficulty of visualizing anatomical structures in obese patients, where excessive subcutaneous adipose tissue obscures sonographic landmarks [42]. CNNs trained on diverse body habitus datasets can enhance image interpretation accuracy by up to 32% in high-BMI cohorts compared to unaided human operators [43]. Furthermore, AI's predictive error correction capabilities mitigate risks associated with anatomical variations. For instance, AI systems can be designed to simulate the clinical consequences of incorrect needle placement (*e.g.*, proximity to a vessel) based on patient-specific anatomical models, enabling trainees to internalize safety protocols before encountering real patients [26, 44]. This symbiosis of technical innovation and clinical pragmatism positions AI-enhanced simulation as a vital tool for overcoming the limitations of traditional apprenticeship models. Moreover, AI systems are increasingly capable of simulating injectate spread patterns, providing feedback on whether the local anesthetic is adequately surrounding the target nerve or potentially diffusing into adjacent tissues, which is critical for block success and avoiding suboptimal outcomes.

3.2 Validation studies: AI-assisted *vs.* traditional training outcomes

3.2.1 Advantages and challenges of regional anesthesia

UGRA is now key in anesthesiology [1, 45]. It offers more benefits than traditional methods. UGRA improves precision in locating anatomical structures, raising nerve block success rates and reducing complications like nerve injury and local anesthetic toxicity [16, 46]. This technique provides real-time views of target nerves and surrounding areas, helping anesthesiologists perform blocks more confidently and accurately. Additionally, UGRA supports multimodal analgesia, improving postoperative pain management, reducing opioid use, and speeding patient recovery [47]. However, UGRA has many challenges [1]. Mastering ultrasound technology is difficult, especially for those used to traditional palpation techniques [48]. Patient with obesity can also be a problem, as it may hide anatomical landmarks and complicate visualization [43]. Furthermore, there are risks of adverse events from ultrasound equipment, such as infections if sterilization protocols aren't followed [48]. Ongoing education and training are needed to ensure the safe and effective use of UGRA in clinical settings.

3.2.2 Limitations of traditional teaching methods

Traditional anesthesiology teaching often uses lectures and hands-on training with cadavers or live patients [49, 50]. Though these methods have long been central to anesthesiology education, they have significant limitations [50]. Cadaveric specimens vary in quality and may not reflect the anatomical variations seen in live patients. This can create a gap between theoretical knowledge and practical application, making it hard for students to apply classroom learning in real-world scenarios. Moreover, traditional methods often lack interactive elements, leading to lower retention and less student enthusiasm [51]. This has highlighted the need for innovative approaches like simulation-based training and virtual learning environments to better prepare students for modern practice [52].

3.2.3 Alignment of demand and technological development

The need for effective pain management in various clinical settings has driven advancements in ultrasound technology and its use in regional anesthesia [53, 54]. As healthcare providers aim to improve patient outcomes and reduce opioid reliance, UGRA has become more prominent [55, 56]. New ultrasound techniques, like fascial plane blocks, offer practitioners additional tools for specific pain management needs, especially in emergency and outpatient settings [55, 56].

Furthermore, integrating AI into UGRA has the potential to improve anatomical structure identification and needle placement accuracy [9, 16]. This technological progress matches the growing focus on personalized medicine, allowing practitioners to tailor anesthetic approaches based on real-time imaging data. The wider availability of ultrasound technology and the rise of telemedicine also enable remote consultations and training, expanding UGRA access to underserved areas [56].

3.3 Implementation challenges in curriculum integration

Despite the technological promise and encouraging early validation data, the integration of AI-enhanced UGRA simulation into standardized curricula faces several significant challenges. The development and procurement of high-fidelity AI simulation platforms represent a substantial financial investment for institutions, potentially limiting accessibility. Effective implementation requires educators themselves to be proficient in both the technology and the pedagogical approach of AI-enhanced simulation, necessitating dedicated faculty development programs. Integrating such technology disrupts traditional apprenticeship models and didactic teaching schedules, requiring careful change management and evidence of clear superior outcomes to gain buy-in from educators and institutions. Ensuring reliable operation of hardware and software, along with data security and privacy for trainee metrics, presents ongoing operational hurdles.

3.4 Design and functionality of simulation platforms

3.4.1 User-friendliness of the user interface

User interface design in simulation platforms is key for boosting learning, especially in medical training [57, 58]. A user-friendly interface has an easy-to-understand layout, simple navigation, and ready access to features. All of these work together to create a more interesting and effective training setting. For example, research shows that when users can interact with simulation platforms without difficulty, their learning outcomes improve significantly [59, 60]. A well-designed interface lessens cognitive load, enabling trainees to concentrate on learning skills, rather than wrestling with the technology [61]. User feedback often points to the importance of clear instructions, responsive controls, and visual aids that guide them through training. In addition, adding elements like real-time feedback and performance tracking within the interface can make users more engaged and motivated. For instance, a study on a haptic robotic trainer for central venous catheterization found that a personalized user interface was crucial for effective learning [62], highlighting the importance of user interface design in simulated ultrasound-guided procedures. This principle directly extends to the design of UGRA simulation platforms. As simulation platforms develop, continuous user feedback should be part of the design process. This ensures interfaces stay in line with user needs and preferences, creating a more effective educational experience.

3.4.2 Importance of real-time feedback mechanisms

Real-time feedback mechanisms are essential for the effectiveness of simulation platforms, especially in medical training where instant skill application is crucial. They give users instant insights into their performance, enabling them to adjust and improve techniques immediately. Research shows that real-time feedback greatly improves learning by reinforcing correct actions and correcting errors as they happen. For example, in UGRA training, participants receiving real-time feedback via a simulation platform had lower error rates and better procedural skills than those without such feedback [63]. This instant reinforcement helps solidify learning and promotes skill retention over time. Moreover, real-time feedback can be customized to individual learner needs, allowing for a personalized training experience that targets specific weaknesses. As technology advances, incorporating sophisticated feedback systems, like those using AI to analyze performance data, can further enhance simulation training effectiveness. This integration not only improves skill acquisition, but also builds learner confidence, preparing them for real-world applications.

To elucidate the practical setup of an AI-enhanced UGRA simulation platform, its core components can be described as an integrated system. Trainees typically interact with a haptic probe that mimics a real ultrasound transducer and a needle controller that provides realistic tactile feedback during virtual tissue puncture. The visual interface displays a simulated ultrasound image, dynamically generated and augmented in real-time by AI with color-coded overlays that identify key anatomical structures, such as nerves (*e.g.*, highlighted in yellow) and blood vessels (*e.g.*, highlighted in red). A separate performance dashboard displays key metrics, such as needle trajectory accuracy, procedure time, and error logs. This entire system is driven by the underlying AI architecture (as depicted in Fig. 2), which continuously analyzes the trainee's actions via motion sensors and adjusts the scenario difficulty. This combination of haptic, visual, and quantitative feedback creates a comprehensive and immersive learning environment that bridges virtual practice and clinical application.

3.4.3 Training effectiveness of combining virtual and real-world scenarios

Combining virtual and real-world training scenarios is a powerful approach in simulation-based education, especially in fields like medicine and surgery [64–66]. This blended learning model uses the strengths of both environments, giving learners a safe space to practice complex procedures while also preparing them for real-life unpredictability. Research shows that trainees engaging in both virtual simulations and hands-on practice perform better and retain skills more than those relying on one method alone [67]. For example, studies on virtual reality training for surgical procedures found that participants who first practiced in a virtual environment made fewer errors and were more precise during actual surgeries [65, 68]. The ability to simulate various clinical scenarios in a controlled setting allows learners to develop critical thinking and decision-making skills without real patient pressures. In addition, the immersive nature of virtual training can boost engagement and motivation, making learning more enjoyable [69, 70]. As institutions adopt this hybrid approach, ongoing research is vital to refine the integration of virtual and real-world training, ensuring learners are well-prepared for professional challenges [71]. The future of medical education lies in effectively combining these training methods to optimize learning and ultimately enhance patient care outcomes.

To operationalize this blended learning, a conceptual workflow for an AI-enhanced UGRA simulation platform is synthesized from the technologies discussed in this review. This system integrates real-time ultrasound image analysis with adaptive scenario generation, enabling trainees to practice both normal and complex anatomical variations (*e.g.*, obese patients, and aberrant vasculature). By combining CNN-driven anatomical recognition, sensor-based performance tracking, and reinforcement learning for risk prediction, the platform dynamically adjusts training complexity based on individual proficiency. Such a design directly aligns with the hybrid training philosophy discussed above, offering a scalable solution to bridge virtual skill acquisition and real-world clinical application (Fig. 3).

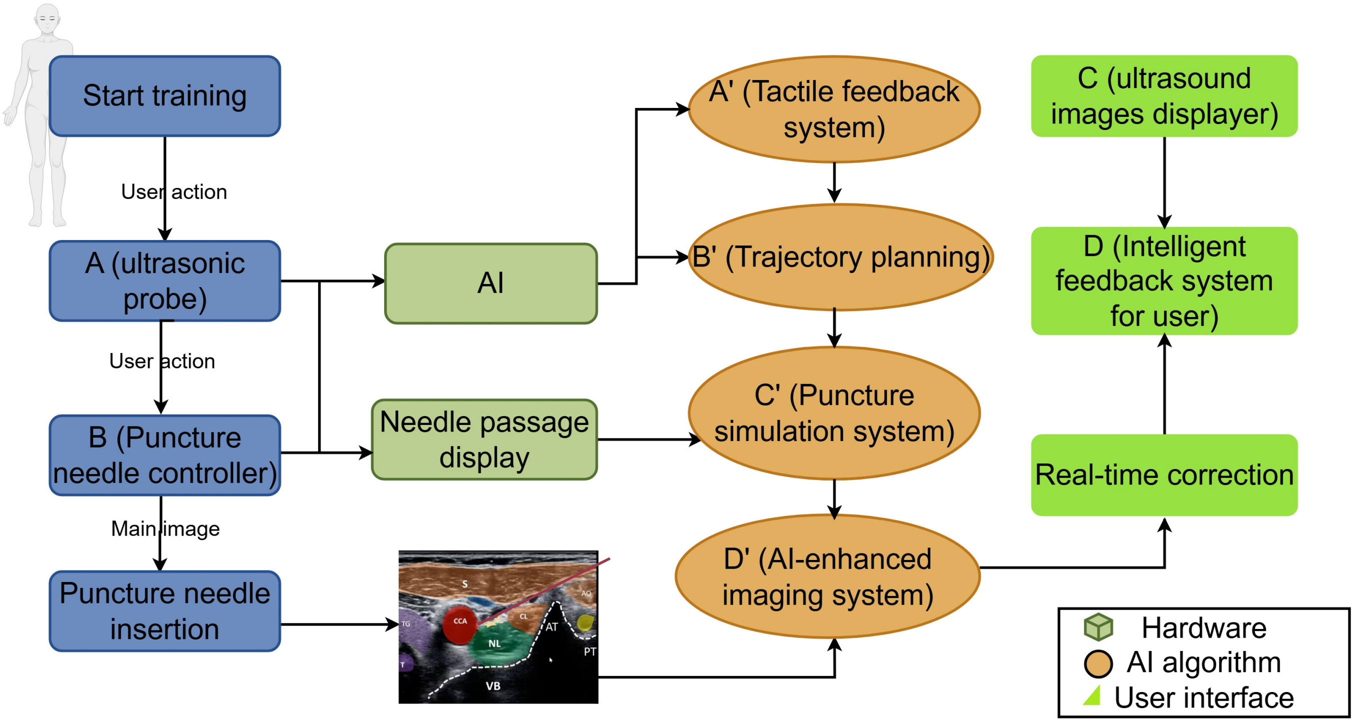

FIGURE 2. Conceptual diagram of the AI-enhanced UGRA simulation platform. This schematic illustrates the integrated system components and their interactions, designed to create an immersive training environment for ultrasound-guided regional anesthesia (UGRA). The platform bridges the gap between virtual practice and clinical application through four key components: A (Haptic Probe): Simulates a real ultrasound probe, providing tactile feedback with force feedback technology to mimic resistance on different tissue surfaces. B (Needle Controller): Reproduces tissue resistance and puncture sensations during needle insertion, including realistic "breakthrough" feelings and safety mechanisms. C (Visual Display): Renders real-time ultrasound images enhanced with AI overlay, using color-coding to identify critical anatomical structures (*e.g.*, nerves in blue, and vessels in red) and display needle trajectory guidance. D (User Interface): Provides performance metrics (*e.g.*, accuracy, time, and angle deviation) and real-time corrective feedback, along with skill progression analysis and personalized training adjustments. The system integrates hardware, AI algorithms, and user interfaces to enable realistic simulation and effective skill development. AI: artificial intelligence; TG: Thyroid Gland; T: Trachea; S: Sternocleidomastoid; CCA: Common Carotid Artery; NL: Longus Colli Muscle; VB: Vertebral Body; CL: Clavicle; AT: Anterior transverse nodule; PT: Postternal nodule.

3.5 Future directions for personalized competency development

In education, particularly medical education, statistical analysis of student skill enhancement is key to evaluating teaching effectiveness. Comparative studies of different teaching methods can measure student progress in knowledge, clinical skills, and confidence [72]. Research shows that students taught with new methods, such as flipped classrooms and simulation-based training, outperform those taught with traditional methods in both theoretical and practical assessments [73]. For example, a study found that students in flipped classrooms scored higher on multiple-choice tests, showing the method's effectiveness in promoting active learning and knowledge retention [74]. Statistical analysis also uses questionnaires to collect student feedback on teaching methods, providing insights into their satisfaction and self-efficacy. Studies have found that students in interactive lecture settings reported higher satisfaction and better learning outcomes than those in traditional lectures [75]. These data help teachers improve their methods and inform administrators' decisions on curriculum reform. Recent pilot studies and randomized trials suggest that AI-enhanced simulation can reduce error rates by up to 40% and improve first-attempt success rates in nerve blocks. However, large-scale RCTs are still needed to confirm these findings and assess long-term clinical impact.

The integration of AI into UGRA simulation platforms represents a transformative advancement in medical training and procedural accuracy. Future iterations of these systems are anticipated to leverage multimodal data fusion, combining real-time ultrasound imaging with haptic feedback, patient-specific anatomical modeling, and adaptive AI algorithms to create hyper-realistic training environments. Enhanced deep learning architectures, such as transformer-based networks and reinforcement learning frameworks, may enable dynamic scenario generation, individualized skill assessment, and predictive error correction tailored to individual learner proficiency.

Academic research should prioritize three key directions: (1) development of explainable AI (XAI) systems to improve clinical trust and educational transparency, (2) integration of multi-omics data for patient-specific risk stratification in simulated scenarios, and (3) validation of long-term skill retention through longitudinal studies. Additionally, addressing ethical considerations in AI bias mitigation and ensuring cross-

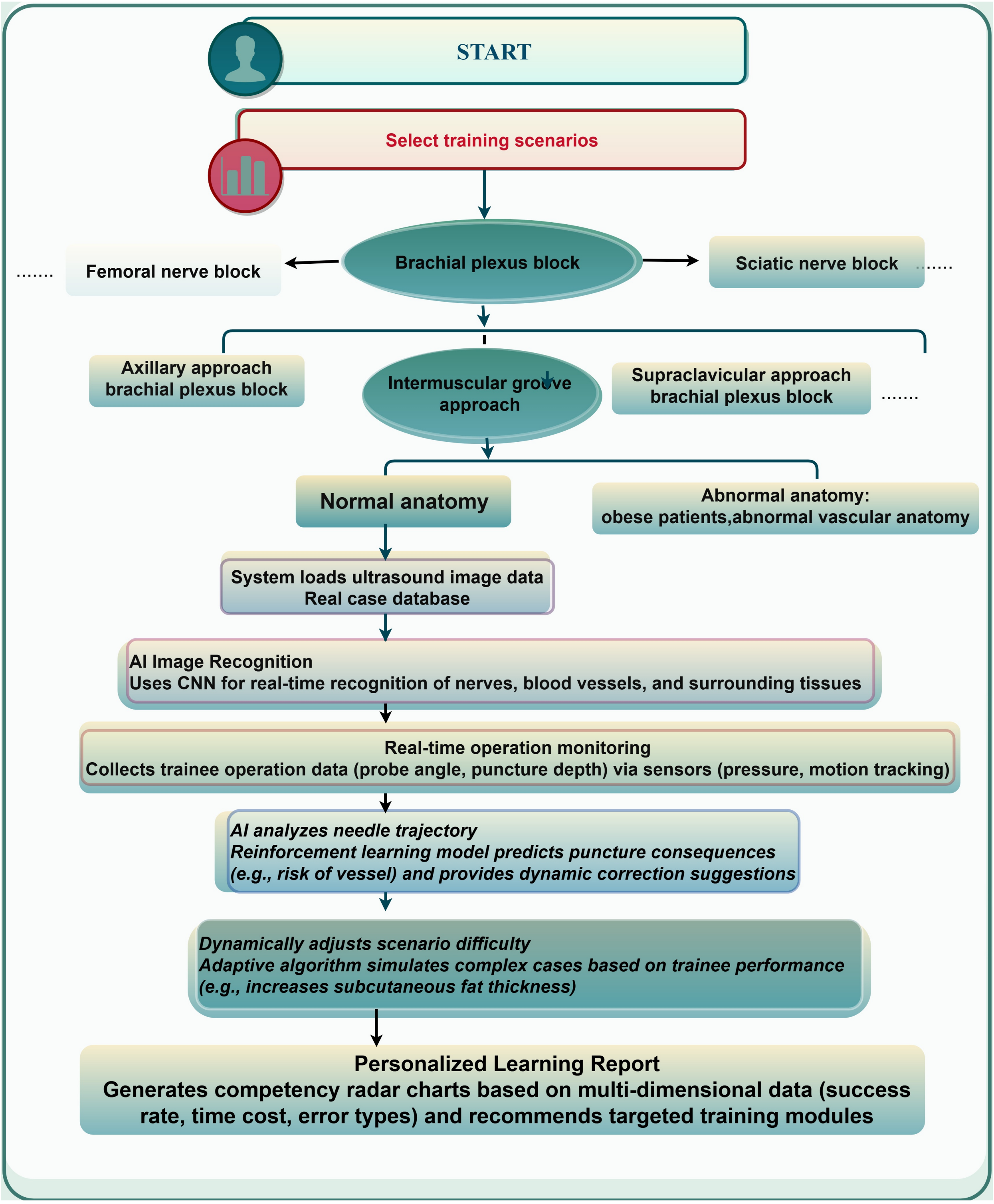

FIGURE 3. Flowchart of the AI-enhanced ultrasound-guided regional anesthesia simulation platform. Focused on brachial plexus block (covering intermuscular groove approach, axillary approach, and supraclavicular approach, *etc.*), the platform expands to regional anesthesia scenarios, such as femoral nerve block and sciatic nerve block, supporting simulations of both normal anatomy and abnormal anatomy (*e.g.*, obese patients, and abnormal vascular anatomy). It loads ultrasound image data and real-case databases, utilizing CNN technology for real-time AI image recognition of nerves, blood vessels, and surrounding tissues. Integrated with pressure and motion-tracking sensors, it collects trainees' operational data (*e.g.*, probe angle, and puncture depth) for real-time operation monitoring. A reinforcement learning model analyzes the needle trajectory, predicts puncture risks (*e.g.*, vessel injury), and offers dynamic correction suggestions. Additionally, an adaptive algorithm adjusts scenario difficulty dynamically based on trainees' performance (*e.g.*, simulating increased subcutaneous fat thickness). Ultimately, multidimensional data—including success rate, time cost, and error types—are used to generate competency radar charts and recommend targeted training modules, bridging the gap between theoretical knowledge and clinical skill transformation. CNN: Convolutional neural network.

population generalizability of training models will be critical for global applicability. Collaborative efforts between computational scientists, anesthesiologists, and medical educators are essential to bridge the translational gap between algorithmic innovation and clinical adoption.

Responsible integration of AI in medical education requires addressing key ethical imperatives: (1) Data security through encryption and regulatory compliance (General Data Protection Regulation/Health Insurance Portability and Accountability Act (GDPR/HIPAA)) for trainee metrics and patient data; (2) Algorithmic fairness via diverse training datasets and continuous auditing to prevent demographic bias; (3) Explainable AI that provides interpretable feedback to overcome "black box" limitations and build trust. Crucially, AI should augment rather than replace expert instruction, preserving human oversight and ultimate clinical responsibility. These foundations are essential for developing trustworthy AI that enhances both education and patient care.

This evolution has the potential to redefine competency-based training paradigms and establish UGRA simulation as a cornerstone of precision medical education, pending validation through rigorous outcome studies. Future studies must rigorously quantify the clinical impact of AI-enhanced simulation on patient outcomes to secure its role in next-generation anesthesiology practice.

Despite the promise of AI-enhanced simulation, several barriers impede widespread adoption, including high initial costs, the need for specialized training for educators, and resistance to integrating technology into traditional training paradigms.

Furthermore, longitudinal studies are urgently required to validate whether skills acquired on AI-enhanced simulation platforms translate into sustained clinical competency and improved patient-centered outcomes, such as reduced complication rates and enhanced block efficacy in real-world practice.

4. Study limitations

As a narrative review, this article does not follow the systematic methodology of a systematic review. The selection of literature was based on the authors' expertise and a non-exhaustive search strategy, which may introduce selection bias.

5. Conclusions

In conclusion, AI-enhanced simulation platforms represent a promising and rapidly evolving development in medical education. While early data from pilot and cohort studies are encouraging, the integration of this technology creates a robust training environment that must be further evaluated through high-quality trials. The medical community should embrace this transformation while mindfully addressing its challenges, with the ultimate goal of improving educational outcomes and enhancing patient care.

ABBREVIATIONS

AI, Artificial intelligence; UGRA, Ultrasound-guided regional anesthesia; CNNs, Convolutional neural networks; ML, Machine learning; DL, Deep learning; RCTs, randomized controlled trials; XAI, explainable Artificial intelligence; IEEE, Institute of Electrical and Electronics Engineers; PICO, Patient/Population, Intervention, Comparison, Outcome; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; MRIs, Magnetic Resonance Imaging; GDPR, General Data Protection Regulation; HIPAA, Health Insurance Portability and Accountability Act.

AVAILABILITY OF DATA AND MATERIALS

All data generated and analyzed during this study are included in this published article.

AUTHOR CONTRIBUTIONS

DMM—provided the overall concept and framework of the manuscript; researched and identified appropriate articles and wrote the paper. WL—was responsible for the visualization. Both authors approved the final version of the manuscript. Both authors have read and agreed to the published version of the manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study did not involve human participants, animal subjects, or clinical data. Ethical approval and consent were therefore not required.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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