integrate preoperative imaging, intraoperative video, and multimodal clinical data to achieve key anatomical structure recognition, surgical workflow analysis, and risk prediction, thereby improving the objectivity and consistency of decision-making (Chevalier et al., 2025). In particular, robotic-assisted surgery generates large volumes of high-quality video and kinematic data, allowing AI to support surgical skill assessment, optimization of operative trajectories, phase recognition, and even partial automation of specific tasks (Knudsen et al., 2024). Preliminary studies suggest that AI-assisted systems can enhance surgical precision, reduce errors, and improve efficiency; however, their clinical application remains at an early stage and is still challenged by limited generalizability, lack of interpretability, and incomplete ethical and regulatory frameworks.

In the field of gynecology, the integration of AI with minimally invasive surgery holds particularly promising potential. Advances in high-definition three-dimensional imaging, augmented reality navigation, and sophisticated robotic platforms have significantly expanded the technical boundaries of minimally invasive surgery, while the incorporation of AI further enhances its precision and reproducibility (Osman et al., 2025; Pavone et al., 2025). Computer vision-based algorithms can identify critical anatomical structures such as the ureter, uterine artery, and pelvic nerves in real time during surgery, thereby reducing the risk of complications. Machine learning models can be used for preoperative risk stratification and individualized surgical planning, as well as for providing dynamic intraoperative decision support (Varghese et al., 2024; Chevalier et al., 2025). In addition, AI enables objective assessment of surgical skills and optimization of training through the analysis of robotic surgical data, promoting quality control and standardization (Knudsen et al., 2024; Pipes et al., 2025). Nevertheless, current research also highlights several limitations in gynecologic AI applications, including small dataset sizes, heterogeneity in algorithms and evaluation systems, and a lack of high-quality clinical evidence, which to some extent restrict their widespread implementation.

This study aims to explore the technical pathways and clinical application progress of artificial intelligence (AI)–assisted minimally invasive gynecologic surgery. By systematically reviewing the current applications of AI in preoperative evaluation, intraoperative navigation, postoperative analysis, and surgical training, it analyzes its potential advantages in improving surgical precision and efficiency, while also summarizing the existing technical and clinical challenges. On this basis, key future directions are further discussed, including multimodal data integration, algorithm optimization, evidence-based evaluation, and standardized implementation. Within the framework of minimally invasive gynecologic surgery (MIGS), this study provides a comprehensive analysis of the application models, clinical value, and existing limitations of AI, and offers perspectives on its future development, with the aim of providing theoretical support and practical reference for advancing gynecologic surgery toward greater precision, intelligence, and personalization.

2 Technical Foundations of Artificial Intelligence and Surgical Application Models

2.1 Core technologies: machine learning, deep learning, and computer vision

The application of artificial intelligence (AI) in surgery is primarily built upon core technologies such as machine learning (ML), deep learning (DL), and computer vision (CV). Machine learning fundamentally involves learning underlying patterns from data without explicit rule-based programming, enabling tasks such as classification, regression, clustering, and prediction. It has therefore been widely applied in perioperative risk assessment, prognosis prediction, resource utilization analysis, and clinical decision support (Varghese et al., 2024). Traditional ML methods, including support vector machines, decision trees, Bayesian networks, random forests, and ensemble learning, are particularly effective in handling structured clinical data. By integrating demographic characteristics, comorbidities, laboratory indicators, and perioperative parameters, these methods can predict surgical duration, postoperative complications, and hospitalization outcomes. However, such approaches typically rely on manual feature engineering and often exhibit limited performance and generalizability when applied to high-dimensional, unstructured data such as surgical images and videos (King et al., 2025).

With advancements in computational power and the accumulation of large-scale datasets, deep learning has emerged as the dominant paradigm in surgical AI. DL utilizes multilayer neural networks to automatically learn hierarchical representations, significantly reducing reliance on handcrafted features and making it particularly