# Artificial intelligence in urology training

## Enhancing annotation, feedback, and evaluation in robotic, laparoscopic, and endoscopic surgery

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## ABSTRACT

**INTRODUCTION:** The integration of artificial intelligence (AI) into surgical training is rapidly evolving, driven by advancements in machine learning. This review aimed to map the current landscape of AI's educational applications in urology.

**METHODS:** A systematic search of MEDLINE, PubMed, Embase, Cochrane, Scopus, and Engineering Village identified studies exploring AI applications in video-based surgical education and assessment. Search terms included AI, urologic procedures, and training/assessment components, and results were screened in Covidence®. AI applications involving urologic procedures were included. For every study, two reviewers independently conducted screening. Data were synthesized thematically to evaluate AI's application in urology training.

**RESULTS:** Our search yielded 2774 studies, of which 59 relevant ones were identified. AI was most frequently applied with robotic-assisted radical prostatectomy (RARP), followed by robotic-assisted partial nephrectomy (RAPN). AI applications were broadly categorized into three domains: 1) annotation, where key anatomy and instruments from procedural videos are labelled; 2) feedback, such as recognizing surgical phases or monitoring surgical events; and 3) evaluation, where the surgical gestures are recognized or evaluated to stratify skill level and predict patient outcomes.

**CONCLUSIONS:** The emergence of AI use in urologic procedures underscores its transformative potential in procedural education and training. AI has wide applications in annotation, feedback, and assessment across different procedures. While prostatectomy dominates in the literature, the adaptability of AI frameworks exists across other urologic procedures. New, commercially available tools demonstrate promising results, making them potentially beneficial additions to urology training programs. Future efforts should focus on multicentric collaboration and longitudinal skill assessments.

## INTRODUCTION

Artificial intelligence (AI) refers to the computational capacity of machines to perform tasks typically associated with human intelligence and cognition. In medicine, AI has gained prominence to enhance diagnostic accuracy, support clinical workflows, and improve patient outcomes. This growth has been driven by major advances in computing power, algorithm design, and the widespread adoption of electronic data handling, which together have produced vast repositories of structured medical data. These datasets now enable the development of predictive models capable of learning from complex patterns.

### AI in surgery

AI has increasingly expanded into surgical practice, with a wide range of applications in video-based procedures. The growing adoption of robotic platforms, such as the Da Vinci system (Intuitive Surgical, Inc.), has further accelerated this trend by generating large-scale datasets.

Emerging studies demonstrate AI's ability to enhance robotic procedures by providing surgical feedback and automated skill assessment. Automated surgical systems that incorporate machine learning are already in trial for non-human subjects.[1] There are already commercially available AI platforms that are being integrated into common procedures, such as inguinal hernia repair.[2] Aside from aiding physicians in the operating theatre, these AI models can address long-standing

## KEY MESSAGES

- We conducted a scoping review of AI applications in urology surgical training; a comprehensive search of six databases, with 2767 studies screened and 59 included.
- AI applications clustered into three domains: 1) annotation (labelling anatomy/instruments); 2) feedback (recognizing phases, monitoring events); and 3) evaluation (gesture recognition, skill stratification, outcome prediction).
- AI demonstrates transformative potential in Canadian urology education; adaptable frameworks extend across robotic and endoscopic procedures.

challenges in surgical education, including subjectivity in skill assessment, inconsistent feedback, and prolonged learning curves. Previous reviews have shown AI's ability to make training more consistent and standardized for trainees.[3]

Urology is a surgical specialty heavily reliant on video-based minimally invasive and robotic techniques, such as robot-assisted prostatectomies, nephrectomies, and endourology. While AI has been explored for various clinical applications in urology, its potential to standardize and improve training remains greatly underexplored in current literature.

Currently, undergraduate and residency training in urology lacks standardization across Canada.[4] A pan-Canadian survey reveals significant variability in urology education, with the lack of a uniform curriculum in medical schools.[5] For urology residents, only 7% of respondents reported that their program had clear criteria to help them progress through the steps of robot-assisted surgery (RAS), and most trainees (81%) felt their residency program should provide them with a formal RAS training program.

The absence of standardized educational objectives in urology training and education programs highlights a unique opportunity to leverage AI in providing more efficient and consistent training frameworks. There is a lack of previous studies that outline the current applications, methodologies, and outcomes of AI for procedural training specific to urology. We aim to address this gap to help create a more standardized training environment for urologic trainees.

To better understand the role of AI in surgical education, concepts like machine learning, deep learning, and computer vision are briefly clarified in Table 1, and the various scopes of AI terminology are depicted in Figure 1.

## METHODS

This review was conducted in accordance with the Preferred Reporting Items for Systematic Review and Meta-Analysis extension for Scoping Reviews (PRISMA-scR) Checklist reporting guidelines. The protocol was registered on OSF (10.17605/OSF.IO/GHUJK).

### Study selection

A comprehensive literature search was performed across six databases (MEDLINE, Cochrane, PubMed, Scopus, Embase, and Engineering Village). Two reviewers conducted the search using predefined keywords related to AI, urology, and surgical training.

The search strategy included the following terms: "Artificial intelligence" OR "AI" AND "video recording" OR "video(s)" AND "surgery" OR "surgical" OR "surgeon" AND "laparoscopy" OR "laparoscopic" AND "endoscopy" OR "endoscopic" AND "Education" OR "Educate" AND "training" OR "trainee(s)" AND "assessment" OR "assess."

The first literature search started in early February 2025 and was completed in late February 2025. The

**Table 1. Brief overview of definitions of AI research terminology[6,7]**

| Term | Definition |
|---|---|
| Machine learning (ML)[6] | ML is a key aspect of AI where algorithms learn patterns from data without explicit programming, enabling systems to improve through experience. ML provides the tools for pattern recognition, which is core to AI's application in medicine. By learning from data, ML algorithms empower AI systems to adapt and improve their performance over time. |
| Deep learning (DL)[6] | DL is a type of machine learning technique using multilayered neural networks called nodes to process complex data (e.g., images/videos), with inspiration from human neural architecture. Examples of deep learning models relevant in medicine include CNNs and the newer vision transformers (ViT) for processing images.[7] |
| Computer vision (CV)[6] | CV is a field of AI that enables machines to interpret visual information, often using deep learning and CNNs. In surgery, this technology allows for the identification of structures from intraoperative images/videos. Applications such as real-time anatomical labelling, workflow segmentation, and gesture recognition can be identified from surgical video data. |

CNN: convolutional neural networks.

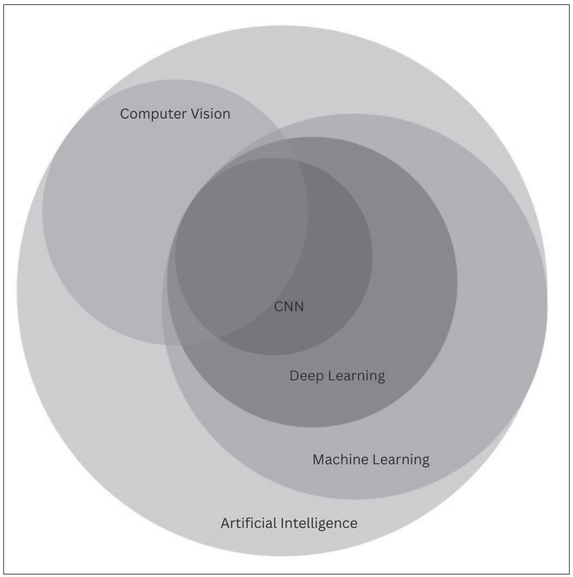


**Figure 1.** The various scopes of artificial intelligence terminology.

second literature search started in August 2025 and was completed in September 2025. Studies were eligible if they involved urology-based laparoscopic or endoscopic procedures (simulations included) and included high-quality surgical data (images, audios, videos). We included both peer-reviewed articles and conference abstracts that described the use of AI for annotation, education, or performance assessment in procedural contexts. We excluded studies solely focusing on diagnosis/prognosis without involving procedures. Studies without results pertaining to an AI model were also excluded.

Study selection occurred in two stages: 1) title and abstract screening conducted independently by four reviewers, with conflicts resolved by consensus; and 2) full-text screening performed by two independent reviewers.

### Data extraction

Only articles deemed eligible for inclusion by consensus were subsequently analyzed for extraction (n=59).[8-66] Abstracts were included, given the novelty of the topic and the observed trends of likely conversion to full-text publications. Three independent reviewers were tasked with performing the data extraction using a standardized form. Data on publication year, procedural intervention, sample size, AI model, AI application, and main reported outcomes were collected.

## RESULTS

The initial search yielded 2774 studies, of which 267 reached full-text screening, and 44 studies were included for final analysis. Through reference screening, we found 12 eligible studies. The updated search resulted in three additional studies. A total of 59 studies, including full-texts (n=50) and abstracts (n=9), were included after a comprehensive search and screening process across MEDLINE, PubMed, Embase, Cochrane, Scopus, and Engineering Village (Figure 2).[8-66]

The majority of studies were published between 2022 and 2025, underscoring a sharp and recent rise in interest towards AI applications within urologic surgical education and training. These studies spanned a wide range of methodologies, including retrospective video analyses, prospective observational studies, and exploratory modelling papers on animals or phantom models, reflecting a field that is rapidly diversifying its research approaches.

Technologically, the majority of models were developed in-house (n=50), with convolutional neural networks (CNN) models dominating due to their proven efficacy in image segmentation tasks. Modified U-Net and ResNet models are often seen. Vision transformers are also emerging as alternatives to CNNs. Commercially available AI products are also seen, although limited (n=9).

In the set of studies, we defined three principal domains that the educational applications of AI broadly belonged to (Supplementary Table 1; available at *cuaj.ca*). The first was annotation (n=22), where models labeled key anatomical structures or surgical instruments in the surgical field to facilitate anatomical education and intraoperative safety in the context of urologic procedures. The second most prevalent domain involved surgical feedback (n=20), which included the procedural phase and event recognition and prediction. The third domain was skill evaluation (n=17), where the developed AI models assessed motions and gestures or predicted clinical outcomes. A visual representation of AI education domains across common urology procedures are seen in Figure 3. Notably, 13 of 17 skill evaluation papers are limited to robotic-assisted radical prostatectomy (RARP) procedures.

## DISCUSSION

To our knowledge, the current article is the first to summarize AI applications specific to urologic procedural training. In the current review of 59 studies, AI's educational potential in urology is observed to be applied in three major categories: annotation, surgical feedback, and skill evaluation.

### Anatomical annotation

Annotation refers to AI's ability to identify and label clinically relevant anatomical features and procedural steps in surgical data represented by videos. In urology, where procedures like prostatectomy and nephrectomy require navigation of complex anatomy through limited visual fields, annotation systems provide crucial spatial orientation. These tools are particularly valuable for trainees learning anatomical relationships and surgeons performing high-risk dissections.

The clinical impact is evident in RARP, where Takeshita et al developed a CNN-based model to help annotate the seminal vesicle and vas deferens to guide dissection, which resulted in a faster recognition time for five urology trainees new to the posterior approach of RARP.[26]

Similarly, on top of anatomical annotation, surgical instruments can be recognized by CNN models. For instance, Pak et al demonstrated remarkable segmentation accuracy (Dice scores 0.93–0.94) for critical structures such as neurovascular bundles and seminal vesicles and surgical instruments with 98% accuracy.[22]

In addition to pure annotation, anatomical prediction was also seen: Bakker et al developed an AI model to estimate surgical urethral length (SUL) on intraoperative RARP videos, supporting surgical planning to optimize postoperative continence outcomes.[9] Their U-Net model achieved SUL predictions with small mean differences (<2 mm) compared to manual annotators.[9]

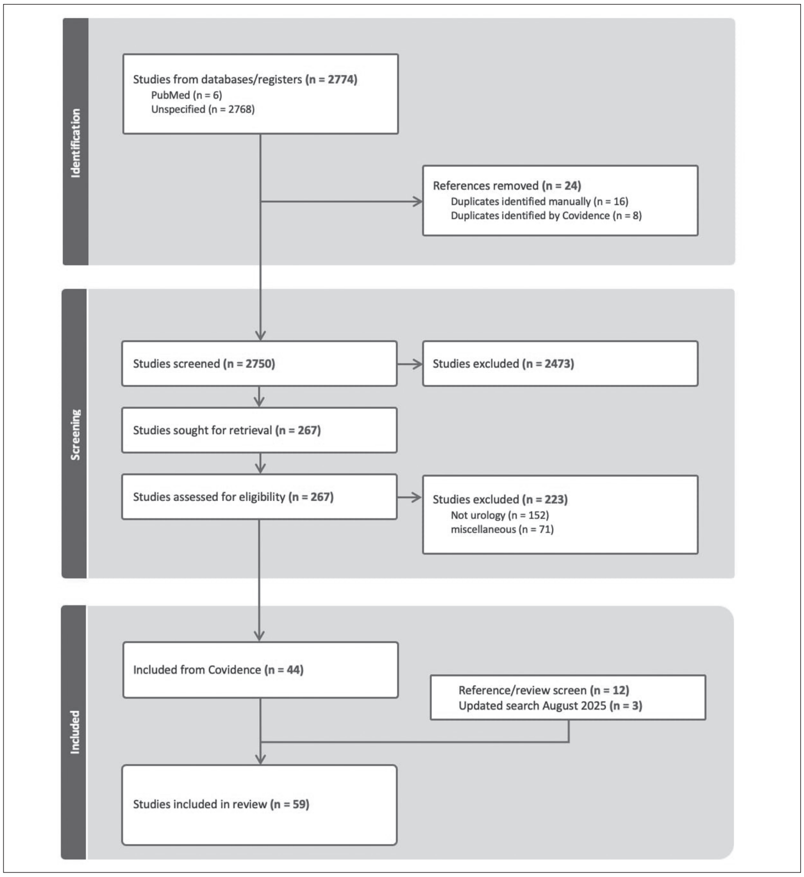


**Figure 2.** Flowchart of screened references and reasons of exclusion.

Annotation is not limited to RARP. Lazo et al developed a model to track hollow lumen in ureteroscopy videos to indicate the passage the instrument should follow, where they achieved a high Dice similarity coefficient for lumen segmentation (0.80).[16] Furthermore, in endoscopic procedures like resectoscopy and ureteroscopy, the ureteric orifice (UO) is a key anatomical landmark. In Peng et al's study, they aimed to create a single-shot detector (SSD) model to identify the UO, which demonstrated a processing time of 25 ms per frame and simultaneously achieved satisfactory recall and specificity.[23] The same group of authors' followup study yielded high test sensitivities on resectoscopy and ureteroscopy video frames in video sequence analysis.[18] The researchers highlighted this model's great potential to serve as a learning and feedback system for new urologists or trainees.[18]

Some studies combined AI anatomical annotation with augmented reality. For procedures like robotic-assisted partial nephrectomy (RAPN), Zhang et al aimed to align preoperative 3D models with intraoperative video.[28] Experimental results have demonstrated that the proposed framework could accurately overlay comprehensive preoperative models on deformable soft organs automatically.[28]

A more recent study tested a similar idea intraoperatively. In Amparore et al's study, AI helped overlay 3D virtual kidney models onto real surgical fields during RAPN.[8] They showed that both CNN-based (iKidney) and CV-based (IGNITE) models showed comparable preoperative and postoperative characteristics, and neither AI resulted in intraoperative or postoperative complications.[8] By creating real-time anatomical overlays, these systems function as a GPS for surgeons in tumor resection.[8]

## Surgical feedback

Feedback systems in urologic surgery encompass video analysis for phase/event identification and intraoperative guidance. These feedback mechanisms serve as essential tools for surgical education and quality improvement. For surgical phase recognition, models like TecNO by Konnai et al demonstrate 94% accuracy in segmenting RARP procedures when analyzing recorded videos, enabling detailed postoperative review and performance benchmarking.[46] Few studies, like one by

Zuluaga et al, have demonstrated promising annotation of surgical phases and intraoperative events in the OR in real-time for RARP and RAPN using a commercially available AI.[49] These studies highlighted that surgical phase recognition AI models allow for detailed review and performance benchmarking for trainees.

Another key application in this category is surgical events like ischemia monitoring in nephrectomies. Ayala et al demonstrated an algorithm that allowed for real-time, contrast-free ischemia tracking in laparoscopic nephrectomies.[30] In almost all patients, they demonstrated perfect separation of ischemic tissue from that corresponding to perfused tissue.[30]

Commercial platforms have also been tested for warm ischemic time. Bobrowski et al used TSE (Touch Surgery™) to estimate warm ischemic time in RAPN and demonstrated that the AI can provide warm ischemia time (WIT) more accurately than surgeon-documented times during RAPN, although variant cases exist.[31] Similarly, another study by Khandekar et al demonstrated similar results with the commercial platform Theator (data beats intuition™).[39] They demonstrated that AI-computed WITs were within 30 s in 97% of the procedures and that the difference between AI-computed WITs was lower than the difference found in operative reports ($p<0.001$).[39]

Notably, relatively more unique studies are seen within AI applications on surgical feedback. For instance, Khanna et al used phase recognition to make operative reports.[40,42] In another example, the urology program at the Mayo Clinic, by Henning et al, used an AI platform to title and index procedures by type in real-time and further annotate urologic surgical videos to indicate surgical steps and intraoperative events.[37] This group used AI to curate videos to create an interactive teaching platform.[37] In a study by Deol et al, the group developed an AI model to aid surgeons in counting surgical instruments.[35] Another unique study, by Kocielnik et al, looked at using AI to help categorize live intraoperative conversations between urology trainers and trainees and link them to behavioral changes.[45]

## Skill evaluation

Evaluation focuses on the quantitative assessment of technical skills through motion and gesture analysis. This pillar is crucial in urology, where subtle differences in instrument handling and tissue manipulation significantly impact clinical outcomes. Modern evaluation systems use advanced computer vision to decode surgical gestures through the identification of fundamental maneuvers like needle driving, suturing, and dissection with remarkable precision.

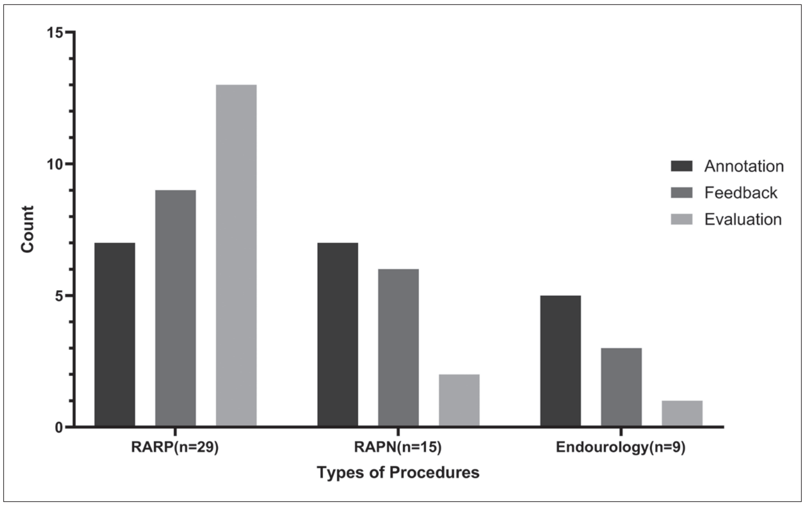


**Figure 3.** Artificial intelligence application domains across RARP, RAPN, and endourology procedures. RARP: robotic-assisted radical prostatectomy; RAPN: robotic-assisted partial nephrectomy.

The EASE system, by Cui et al, exemplifies this approach, analyzing 3448 stitches across 156 VR simulations to evaluate six distinct suturing subskills through their kinematic signatures, achieving an area under the curve (AUC) of 0.70 in predicting surgical competency.[52] Similarly, Wang et al developed multitask CNNs that evaluates RAPN and RARP performance by tracking instrument movements, demonstrating good correlation of specific gesture patterns with Global Evaluative Assessment of Robotic Skills (GEARS) and Objective Structured Assessment of Technical Skills (OSATS) scores.[64,65]

AI could also link gestures with clinical outcomes; for instance, Hung et al presented a machine-learning method of processing automated performance metrics to evaluate surgical performance and predict length of stay after RARP.[54] In another study, the DeepSurv model by Hung et al, demonstrated prediction of urinary continence recovery by using 492 automated performance metrics from robotic console data.[55]

Similar applications can be used for training urologists; Ma et al developed a vision transformer-based model to evaluate vesicourethral anastomosis during RARP.[60] The AI assessed needle handling and driving by analyzing trainee performance videos, generating individualized feedback.[60] Results showed statistically significant improvement ($p=0.018$) in needle handling scores among novices receiving AI-generated feedback.[60] Furthermore, objective performance scoring is gaining traction as an educational tool. The multilayered approach to feedback of combining retrospective video review with live performance metrics creates comprehensive opportunities for skill development and error prevention in urologic training.

Such an assessment application is not limited to robot-assisted surgeries. To monitor ureteroscopy skill, Valovska et al developed a novel AI-based scoring system, the Composite Ureteroscopic Efficiency Score (CUES), incorporating many parameters to quantify ureteroscopy skill.[63] In the study, the scoring system effectively differentiated between residents and attending surgeons (p=0.04), while also tracking skill progression across repeated attempts.[63]

These motion-based evaluation tools are establishing a new paradigm of competency-based training in urology, where progression is guided by quantitative performance metrics rather than subjective experience measures.

## AI models in urologic education

### Technological studies

There are many AI architectures in these studies. Most algorithms are built off the backbones of CNN architectures. While different studies compared different architectures of models, a common theme seen in studies is the choice between vision transformer models and CNN-based models. Vision transformers, which are emerging, show promising results, as demonstrated by Kiyasseh et al, due to analysis from their self-attention mechanism and their flexibility on the number of frames of video input;[56] however, in another study, Pak et al concluded that CNN models are still better than vision transformer models in unusual cases.[22] Variations exist between and among the various architectures, and following this trend, we are expecting more comparative studies for the optimal AI architecture for specific tasks.

### Commercial AI platforms

Importantly, commercial AI platforms are transitioning into real-time clinical integration. An algorithm by Touch Surgery™ was able to estimate WIT in RAPN more accurately than surgeon reports.[31] Zuluaga et al employed Theator (data beats intuition™)'s Video Transformer Network during live RARP and RAPN procedures, achieving subsecond latency in annotating surgical steps, safety-critical structures, and events such as hemorrhage.[49] Although limited to two surgeries, their study nonetheless demonstrated the feasibility of deploying AI as a live educational tool.[49]

In another study, Henning et al leveraged Theator (data beats intuition™)'s indexing capabilities to create a secure, organized surgical video repository for laparoscopic and robotic urologic procedures.[37] This AI platform enabled residents to efficiently review specific procedural components, fostering targeted learning.[37]

## Future directions

While current educational applications of AI in urology have demonstrated promising feasibility and accuracy, its full potential is yet to be discovered. One of the most pressing needs is the scaling of AI models through multicentric collaboration. At present, most studies rely on small, single-institution datasets, inherently limiting model generalizability and robustness. Establishing diverse and ethically curated surgical video repositories across academic centers would allow AI models to train from minor procedural differences. This is particularly critical in urology, where operative nuances and equipment settings subtly alter anatomy visualization and instrument handling. In addition, the lack of longitudinal studies highlights the need for followup research on how AI training impacts long-term skill development.

Compared to countries like the U.S., there exists a lack of AI studies and applications in Canada pertaining to urology education. Given the reported inconsistency in urology training programs from previous surveys, more programs could consider incorporating available AI systems to aid training residents and fellows.

Another transformative opportunity lies in the integration of AI with surgical simulators and robotic consoles. Simulation remains a cornerstone of surgical education, particularly as work-hour restrictions limit operative exposure. Embedding AI-driven anatomical annotation, gesture recognition, and real-time feedback into simulators could replicate real-case complexity while enabling immediate, objective skill refinement for trainees.

Lastly, given the feasibility of many of the AI models, there are more opportunities to assess longitudinal educational outcomes; we expect more studies on how annotation, feedback, and evaluation AI tools can be translated into measurable improvements in urologic trainee competency and patient outcomes.

## Limitations

This review is limited by the heterogeneity of the primary outcomes and the early-stage nature of all the included studies. Most included studies were conducted at single institutions and are affected by small sample sizes and short timeframes. Some studies are still in the abstract stage with limited details. These factors reduce the generalizability and translational potential. In addition, the methodologic rigor and validation of AI models have not been consistently evaluated throughout the present studies, although tools like APPRAISE-AI or TRIPOD-AI could be helpful frameworks for certain studies to assess the quality of AI. There is also a lack of standardized benchmarks for evaluating AI systems in surgical education, making it difficult to compare performance across many different AI models.

## CONCLUSIONS

AI has shown clear potential to strengthen urologic training by providing objective annotation of anatomy, surgical event feedback, and reproducible evaluation of technical skills. These three domains can help address long-standing gaps in surgical education, including variability in feedback and subjectivity in assessment. Current findings establish feasibility, but further progress will depend on developing large, multicenter datasets, validating performance longitudinally, and integrating AI tools into simulators and robotic platforms to help create a more efficient way to standardize training and improve technical proficiency in urology.

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This paper has been peer-reviewed.

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