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REVIEW

The Use of Artificial Intelligence in Urologic Oncology: Current Insights and Challenges

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Abstract: Artificial intelligence (AI) is increasingly influencing the field of urologic oncology, offering novel tools to support for clinical decision-making, enhance diagnostic precision, and assist in surgical and pathological workflows. Machine learning (ML) and deep learning (DL) approaches—artificial neural networks, particularly convutional ones—have demonstrated potential across various urologic malignancies, with applications ranging from imaging interpretation and tumor grading to risk stratification and operative planning. While prostate cancer remains the most explored domain, growing interest surrounds AI's use in bladder and renal tumors, and more recently in testicular and penile cancers. Moreover, the integration of AI into robotic surgery and medical writing is opening new frontiers in performance evaluation and patient communication. Despite these advances, critical limitations persist. Issues such as data heterogeneity, lack of external validation, ethical and legal ambiguity, and algorithmic bias continue to hinder widespread adoption. This narrative review examines current developments in AI across major genitourinary cancers, highlighting both clinical opportunities and unresolved challenges in translating these technologies into practice.

Keywords: artificial intelligence, machine learning, prostate cancer, urothelial cancer, renal cancer, robotic surgery

Introduction

Artificial intelligence (AI) refers to the ability of machines to perform tasks that typically require human cognition.[1]

The roots of AI can be traced back to the mid-20th century, notably through the pioneering work of Alan Turing.[2] Since then, progress in computational power, data storage, and algorithmic development has enabled the practical implementation of AI.[3] This so-called "fourth industrial revolution" is not only transforming industries but also challenging clinicians to rethink workflows and decision-making models in healthcare. Its increasing integration into medicine is reshaping diagnostics, treatment planning and surgical practice.[4]

Among medical specialties, oncologic urology is experiencing a remarkable technological transformation with AI playing a central role in this progress and contributing to improvements in patient care.[5,6] AI focuses on creating algorithms that enable machines to reason and perform cognitive functions, such as problem-solving, object and language recognition and decision-making.[7]

Artificial intelligence, machine learning (ML), and deep learning (DL) can be conceptualized as nested matryoshka dolls.[8] Traditional ML depends on manually designed features, like color or texture, while DL specifically focuses on large-scale neural networks, designed to process images, sounds, videos, and other complex data types;[8] this capability allows DL to uncover complex patterns and details that are challenging for humans to detect.[9]

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Artificial Neural Networks (ANNs) including Convolutional Neural Networks (CNNs) are key subfields of ML with CNNs representing a more advanced, domain-specific variation optimized for high-dimensional data such as images and videos.[10]

Despite continuous progress, urologic oncology still faces several critical unmet needs. These include reducing over-diagnosis and overtreatment, improving diagnostic and surgical precision,[11] minimizing the learning curve for complex procedures,[12] and supporting tailored clinical and therapeutic pathways. Equally important is enhancing patient education,[13] reducing bureaucratic burdens on clinicians, and optimizing outpatient workflow and resource allocation.[14,15]

Artificial intelligence (AI) is uniquely positioned to address many of these challenges by analyzing complex datasets, identifying clinically relevant patterns, and assisting in both decision-making and communication.[7]

This narrative review addresses these challenges by outlining current AI applications in urologic oncology, critically assessing their limitations, and identifying concrete opportunities for clinical integration.

This article is intended as a narrative review rather than a systematic analysis. Accordingly, references were selected based on their clinical relevance, novelty, and impact in the field of urologic oncology, rather than through a structured PRISMA-based search strategy.

General Framework for AI in Urologic Oncology

Urologic cancers constitute a significant portion of the global cancer burden. According to GLOBOCAN 2020, prostate cancer ranks as the fourth most commonly diagnosed cancer worldwide, with approximately 1.4 million new cases, while bladder, with among 614 thousands, and kidney cancers, with among 435 thousands, are also among the top ten in incidence.[16] In Italy, genitourinary cancers account for about 20% of all malignancies, with 2022 estimates indicating 40,500 new cases of prostate cancer, 29,200 of bladder cancer, 12,600 of kidney cancer, 2,300 of testicular cancer, and 500 of penile cancer.[17]

Urology is a medical specialty that has evolved rapidly throughout history and continues to advance by incorporating innovative technologies to improve patient care and outcomes.[18]

As a result of these advancements, AI is increasingly being used to diagnose and manage urological diseases. One of the key advantages of AI lies in its ability to efficiently and accurately analyze vast amounts of clinical and imaging data.[19] Among genitourinary malignancies, artificial intelligence has been most extensively applied and studied in prostate, bladder, and renal cancers, where substantial clinical and imaging datasets are available. In contrast, the application of AI in testicular and penile cancers remains limited, reflecting the relative scarcity of data and lower incidence of these tumor types in the general population.

By identifying intricate patterns and subtle details in patient information, machine learning (ML) algorithms assist physicians in early detection, risk evaluation, and personalized treatment planning.[19] Despite growing interest in AI applications for urologic cancers, current studies exhibit several important methodological limitations that hinder broader clinical translation. Many models are validated only on internal datasets, without external validation or comparison to traditional statistical approaches. In addition, substantial variability in data quality, training protocols and algorithm types further limits the reproducibility and generalizability of the results.

The reviewed studies demonstrate promising advances in the application of machine learning (ML) for the diagnosis, classification, and outcome prediction of urologic cancers. Many report high performance metrics, often exceeding those of traditional statistical models, particularly in image-based tasks. However, several limitations persist. A substantial proportion of studies lack external validation, rely on retrospective single-institution datasets, or use heterogeneous methodologies that complicate cross-comparison. Furthermore, few studies assess clinical implementation or cost-effectiveness.

Future research should prioritize multicenter collaborations, inclusion of non-Western populations, external validation of models, and direct comparisons between AI and conventional clinical tools. Addressing these gaps will be essential for translating ML applications into routine clinical practice.

Diagnosis and Medical Treatment of Main Urological Malignancies

Prostate Cancer

Prostate cancer (PCa) is the most common malignancy among men, accounting for 288,300 new cases (29% of all male cancers) and 34,700 deaths (11% of all cancer-related deaths) in the United States in 2023.[20]

Table 1 and Table 2 provide a comprehensive overview of the clinical pipeline of artificial intelligence applications in prostate cancer. Table 1 summarizes the main studies, including AI models, study designs, and performance metrics, while Table 2 illustrates the step-by-step integration of AI tools across the diagnostic and therapeutic pathway.

The diagnosis of PCa generally begins with a biopsy, with or without performing a prostate multiparametric MRI (mpMRI),[30] prompted by initial suspicion due to elevated prostate-specific antigen (PSA) levels.

Arun Seetharaman et al developed the Stanford Prostate Cancer Network (SPCNet) which is a convolutional neural network (CNN) model designed to differentiate aggressive cancer, indolent cancer, and normal tissue on MRI.[21] The model's evaluation was conducted on both pixel and lesion levels in a cohort of 322 patients, including six with normal MRI scans and no cancer, 23 who had undergone radical prostatectomy, and 293 who underwent biopsy.[21] It was trained using data from 78 patients who underwent radical prostatectomy and 24 individuals without prostate cancer.[21] The model identified clinically significant lesions with an area under the receiver operating characteristic curve of 0.75 in radical prostatectomy patients and 0.80 in biopsy patients. Additionally, it detected up to 18% of lesions missed by radiologists, demonstrating sensitivity and specificity comparable to those of radiologists in identifying clinically significant cancer.[21] This model holds promise for aiding physicians in precisely targeting the aggressive components of prostate cancer during biopsy or focal treatments.[21]

To confirm this thesis, *Anindo Saha et al* evaluated an AI system for detecting clinically significant prostate cancer on MRI, comparing its performance to radiologists using PI-RADS 2.1 and standard multidisciplinary care. The AI system was trained and externally validated using a dataset of over 10,000 MRI scans.[22] In a test cohort of 400 cases, the AI outperformed radiologists with a higher area under the receiver operating characteristic (AUROCDAS (0.91 vs 0.86) and detected 6.8% more significant cancers at the same specificity.[22] However, in a larger cohort of 1000 cases, it did not confirm non-inferiority to standard multidisciplinary readings.[22] These results suggest AI could enhance prostate cancer diagnostics, but further clinical validation is required.[22]

Also Rafiqul Islam et al in his study explored machine learning-based approaches to detect prostate cancer using MRI images.[23] It evaluated deep learning models (VGG16, VGG19, ResNet50, and ResNet50V2) for feature extraction and

Table 1 Summary of Principal Articles Regarding AI Applied in Prostate Cancer

Author and Year	Project Title	Study Type	AI Technique Used	Performance Metrics	Limitations
Seetharaman et al, 2021[21]	Stanford Prostate Cancer Network (SPCNet)	Retrospective diagnostic study	Convolutional Neural Network (CNN)	AUC: 0.75–0.80	Limited external validation
Saha et al, 2023[22]	AI for detecting clinically significant PCa	External validation study	AI-based MRI analysis model	AUROC: 0.91 (AI) vs 0.86 (radiologists)	Did not confirm non-inferiority in larger cohort
Islam et al, 2023[23]	ML-based PCa detection from MRI	Internal validation only	Deep learning (ResNet50, VGG16, etc).	Accuracy: 99.64% (ResNet50)	No external validation
Bulten et al, 2023[24]	PANDA Challenge	Multicenter international challenge	Multiple algorithms (ML/DL)	Concordance: 0.862–0.868	Highly curated data; potential selection bias
Bianchi et al, 2023[25]	Graph Neural Networks in PCa detection	Retrospective study	Graph Neural Networks (GNN), DAS-MIL	AUC: 0.93, Accuracy: 0.86	Internal dataset; lack of clinical validation
Rana et al, 2020[26]	Computationally generated H&E staining	Cross-sectional study	Conditional GANs (cGANs)	SSIM: 0.900–0.902	Feasibility study only; limited sample size
Tolkach et al, 2023[27]	AI-assisted pathology in PCa	Validation study	AI with false-positive flagging	Not explicitly reported	Evaluation based on expert consensus
Zhu et al, 2024[28]	Paige Prostate AI Model	Regulatory-grade validation	MIL-RNN	AUC: 0.99 (test), 0.93 (external)	Potential generalizability issues
Hung et al, 2023[29]	DeepSurv model for continence prediction	Prospective cohort study	Deep learning (DeepSurv)	Continence prediction AUC not specified	APMs applicability may vary

Table 2 Pipeline of the Clinical Application of AI Tools in the Flow Chart of Diagnosis, Treatment and Therapy for Prostate Cancer

Clinical Phase	**Primary Objectives**	**Representative AI Solutions (Latest Peer-Reviewed Work)**	**Anticipated Clinical Impact**
Triage & pre-diagnostic counselling	• Identify men at clinically significant risk• Explain the care pathway and available options	• *SAHA* system (*Saha* 2023)[22] – high AUROC on MRI data• **SPCNet** (*Seetharaman* 2021)[21]	• Personalised risk quantification• Better-informed consent for biopsy versus active monitoring
Multiparametric MRI (mpMRI)	• Detect suspicious lesions• Assign consistent PI-RADS category	• **SPCNet** (*Seetharaman* 2021)[21]• ML-MRI models (*Islam* 2023, ResNet-50 backbone)[23]	• Automated segmentation: aggressive vs indolent areas• Reduced inter-reader variability
Biopsy decision and targeted sampling	• Plan lesion-targeted cores• Decide whether systematic biopsy is needed	• Combined output from phases 1 and 2	• Data-driven risk stratification → fewer unnecessary biopsies
Digital histopathology	• Differentiate cancer from benign tissue• Preliminary Gleason grading	• PANDA-challenge ensemble (*Bulten* 2023)[24]• **Paige Prostate** MIL-RNN (*Zhu* 2024, AUC 0.99)[28]	• Whole-slide screening at expert level• Shorter laboratory turn-around-time (TAT)
Assisted pathology reporting	• Confirm/refine Gleason score• Flag ambiguous regions	• False-positive alerting (*Tolkach* 2023)[27]• GNN + DAS-MIL (*Bianchi* 2023)[25]	• Pathologist re-review of "borderline" areas• Higher sensitivity for cribriform patterns
Laboratory workflow optimisation	• Accelerate staining, cut costs, shorten TAT	• cGAN-based virtual H&E generation (*Rana* 2020)[26]	• In-silico H&E from unstained tissue → eliminates physical staining steps
Prognostic stratification and therapy selection	• Choose between active surveillance, radiotherapy, RARP, etc.	• Integrated dashboard aggregating phase-2-to-5 scores	• Tumour board receives unified, explainable metrics for shared decision-making
Robot-assisted radical prostatectomy (RARP)	• Personalised pre-operative briefing on functional outcomes	• **DeepSurv** continence-recovery model (*Hung* 2023)[29]	• 3- to 12-month continence probability → guides counselling and pre-habilitation
Follow-up and quality cycle	• Long-term PSA monitoring and outcome feedback	• Institutional registries continuously retrain models	• Progressive improvement of predictive performance

applied random forest classification to distinguish healthy from cancerous prostate tissues.[23] ResNet50 achieved the highest accuracy (99.64%).[23] However, this result was obtained using internal validation only, without testing on independent datasets, which limits its immediate applicability in clinical settings.[23]

Treatment strategies for localized PCa are determined based on the pathological analysis of biopsy samples. Pathologists diagnose prostate cancer and assign a Gleason grade group (GG) by examining hematoxylin and eosin (H&E)-stained tissue samples.[31] AI has shown potential in diagnosing and grading prostate cancer, but its application has been limited by isolated studies with poor generalization across multinational cohorts, posing a major barrier to clinical integration. *Bulten et al* aimed to overcome these limitations by fostering collaborative development of AI algorithms for prostate biopsy analysis, ensuring reproducible and validated assessment across international datasets.[32,33]

To achieve this, the PANDA challenge was launched as the largest pathology competition to date.[24] Algorithms trained on 10,616 prostate biopsy samples from multiple centers achieved expert-level accuracy, with concordance scores of 0.862 and 0.868 in two independent cross-continental validation sets, demonstrating AI models performance comparable to that of expert uropathologists.[24]

According to a work made by *G. Bianchi et al* AI integration, particularly using Graph Neural Networks (GNNs) and the Distilling Across Scales for MIL (DAS-MIL) algorithm, enhances tumor detection without pixel-level annotations.[25] In his study of 506 biopsies, the model achieved an AUC of 0.93 and an accuracy of 0.86.[25]

AI can address a wide range of tasks beyond diagnosis and grading including measuring cancer length and volume,[34] quantifying the percentage of Gleason pattern,[35] identifying and assessing perineural invasion,[36] quantifying immunohistochemistry (IHC) staining,[37] and detecting and measuring cribriform patterns.[38] The introduction of high-throughput automated pathology slide scanners is paving the way for the full digitization of pathology laboratories, expected to become a reality in the near future.[39]

AI can also enhance pathology laboratory workflows by identifying ambiguous cases that require additional IHC staining and automatically initiating these requests before pathologist review, thereby reducing turnaround times.[14] Additionally, AI can perform fully automated quality control of Whole Slide Imaging (WSI) scans, detecting those that may need re-scanning or re-staining to improve quality.[40] In a cutting-edge study, Rana et al explored the application of computationally generated H&E staining to unstained prostate biopsy images, showing that the algorithm-generated images could accurately replicate prostate tumor characteristics and be used for pathological diagnosis, thus facilitating the early detection of abnormalities in unstained tissue biopsies.[26] Their work was a cross-sectional study in which conditional Generative Adversarial Networks (cGANs) were trained to convert unstained biopsy images into computationally H&E-stained images.[26] The Structural Similarity Index Measure (SSIM) ranges from −1 to 1, where:

1 indicates that the two images are identical, 0 signifies no structural similarity and negative values indicate significant structural differences. The results obtained by *Rana et al* showed high similarity between computationally and physically H&E-stained images with a SSIM: 0.902.[26] While the reverse-staining cGAN restored images to their original unstained form with comparable accuracy (SSIM: 0.900).[26]

Although AI has made significant advancements, it remains susceptible to potential flaws or biases that can result in missed or incorrect diagnoses; However, even AI-generated misdiagnoses can be beneficial.[26] In the study of *Tolkach et al*, pathologists found false-positive alerts from AI useful, as these flagged areas that warranted closer examination and additional immunostaining for more accurate evaluation.[27]

There is a risk that pathologists might overly rely on AI predictions without critically evaluating them, raising concerns about potential overdependence and the compromise of diagnostic skills, which highlights the need for continuous monitoring of pathology labs using AI tools—similar to post-marketing surveillance for new drugs—to evaluate how pathologists interact with AI-generated results and to assess the broader impact of AI on clinical practice.[39]

Moreover, AI has shown significant potential in the field of medicine, particularly in the interpretation of medical images.

In the context of prostate cancer pathology, the US Food and Drug Administration (FDA) has authorized the use of Paige Prostate, a model designed to differentiate benign prostate biopsy samples from those indicative of suspected PCa.[28] This model leveraged multiple instance learning with a recurrent neural network (MIL-RNN) to train on 12,132 whole slide images (WSIs), using pathology report diagnoses as labels; it achieved an impressive area under the curve (AUC) of 0.99 on the test set and 0.93 on an independent external validation set of over 12,000 slides.[28]

Treatment options for localized prostate cancer include active surveillance, ablative radiotherapy, and radical prostatectomy.[41] Urinary incontinence and erectile dysfunction are among the most common adverse effects following robot-assisted radical prostatectomy (RARP).[42,43] *Hung et al* developed a deep learning model (DeepSurv) to predict urinary continence recovery after RARP using automated performance metrics (APMs) collected from 100 RARPs and clinicopathological data, derived from computer-based data recording devices.[29] Features were ranked and a heavier score was addressed to each one based on their importance in predicting continence. The top five ranked features were then used to classify surgeons into two groups: the four highest-scoring surgeons were categorized as "Group 1/APMs" (more efficient APMs), while the others were placed in "Group 2/APMs" (less efficient APMs).[29] The study showed APMs as stronger predictors than clinicopathological features. In this study urinary continence was achieved in 79 patients (79%) after a median of 126 days.[29] Particularly higher urinary continence rates at three and six months post-surgery were detected in patients classified as "Group 1/APM" (47.5% vs 36.7%, p=0.034, and 68.3% vs 59.2%, p=0.047, respectively).[29] So this model is found to be a reliable predictor factor compared to clinicopathological features alone.[29]

Urothelial Cancer

Bladder cancer (BC) ranks as the seventh most frequently diagnosed cancer among men globally and the tenth most common when considering both sexes.[44,45]

Table 3 provides a summary of the principal studies evaluating the application of artificial intelligence in urothelial cancer, including study design, AI techniques, performance metrics, and main limitations.

Additionally, although less common, the occurrence of aggressive upper tract urothelial carcinoma is on the rise, leading to a growing number of cases involving locally advanced and high-grade tumors.[53]

AI plays a role in medical imaging, particularly computed tomography (CT) scans and magnetic resonance imaging (MRI), both of which are essential for UC diagnosis and prognosis.[54] Several studies have demonstrated AI's potentiality in this field. *Xu et al* developed machine learning algorithms based on radiomic features derived from multiparametric MRI (mpMRI) to differentiate bladder tumors from normal bladder wall.[46] Similarly, *Garapati et al* employed morphological and textural features from CT urography to determine the stage of bladder cancer.[47]

AI could be a helpful tool in detecting bladder cancer and staging tumors. In fact, *Ikeda et al* used AI-assisted cystoscopy, which has demonstrated high accuracy in diagnosing bladder cancer by identifying subtle changes in the bladder wall.[48] They developed a CNN-based system trained on 2102 cystoscopic images (1671 normal and 431 tumor lesions), achieving a sensitivity of 89.7% and a specificity of 94% in distinguishing normal tissue from tumor lesions.[48]

Moreover, AI-based analysis of cystoscopic images has demonstrated improved tumor clearance during transurethral resection of the bladder.[55] The algorithm designed by *Ibrahim Fahoum et al* has the potential to significantly assist in accurately identifying muscularis propria invasion by replicating the analytical approach of a pathologist.[49] This AI-driven approach could enhance the accuracy of bladder cancer diagnosis and treatment.[56]

The application of AI is not limited to just image analysis, but it could be also applied in genomics. AI-based studies aim to identify key genetic variants linked to UC, classify molecular subtypes of the disease, and explore pharmacogenomic approaches to determine which subtypes might respond to specific chemotherapy regimens.[57,58] Most genomic studies utilize gene expression profiles or DNA/RNA sequencing data in AI models to predict prognosis, such as risks of disease progression, recurrence, or survival.[57] However, the application of AI to predict treatment responses based on genetic data remains limited and further studies are warranted.

A systematic review and meta-analysis conducted by *Chunlei He et al* evaluated 21 studies that applied image-based AI models—including CT, MRI, radiomics, and deep learning—to predict muscle-invasive bladder cancer (MIBC), analyzing data from a total of 4,256 patients.[50] Seventeen studies were included in the pooled analysis, which showed promising diagnostic accuracy (AUC up to 0.92 for MRI and 0.91 for deep learning models). Despite these encouraging results, the study highlighted substantial limitations in methodological and reporting quality, as assessed by CLAIM, RQS, and PROBAST, with all models carrying a high risk of bias.[50]

A systematic review and meta-analysis conducted by *Caio Vinícius Suartz et al* evaluated the performance of machine learning models in predicting response to neoadjuvant cisplatin-based chemotherapy (NAC) in patients with MIBC.[51] From 12 studies (1,523 patients), four were included in the meta-analysis, reporting a sensitivity of 0.62 and specificity of 0.82. ML models using CT, genomic, and pathological data showed promising predictive ability, although further standardization is needed to improve reproducibility and clinical applicability.[51]

A multicenter study developed and validated AI-based histologic assays to predict recurrence, progression, BCG-unresponsive disease, and need for cystectomy in patients with high-risk non–muscle-invasive bladder cancer (NMIBC) treated with intravesical BCG.[52] Using digitized pathology slides and clinical data from 944 patients across 12 centers, the AI models accurately stratified patients into high- and low-risk groups, providing prognostic information beyond traditional clinicopathologic factors.[52] High-risk classifications were strongly associated with worse outcomes, including shorter recurrence-free and progression-free survival and higher likelihood of cystectomy.[52]

Renal Cancer

Renal cell carcinoma (RCC) is the sixth most frequently diagnosed cancer in men and the eighth in women worldwide, accounting for 5% of all cancer cases in men and 3% in women.[59]

Table 3 Summary of Principal Articles Regarding AI Applied in Urothelial Cancer

Author and Year	Project Title	Study Type	AI Technique Used	Performance Metrics	Limitations
Xu et al, 2017[46]	Radiomic features for bladder tumor detection	Retrospective imaging study	Machine learning on mpMRI radiomics	Not explicitly quantified	Lack of external validation
Garapati et al, 2017[47]	CT-based staging of bladder cancer	Imaging-based study	ML with CT morphological/textural features	Not explicitly quantified	Study limited to CT urography data
Ikeda et al, 2023[48]	AI-enhanced cystoscopic tumor detection	Image classification study	CNN on cystoscopy images	Sensitivity: 89.7%, Specificity: 94%	Internal dataset only
Fahoum et al, 2023[49]	AI-assisted muscularis propria invasion detection	Histopathological diagnostic study	AI model replicating pathologist analysis	Not explicitly quantified	Validation by expert consensus; limited cohort
He et al, 2024[50]	Accuracy of AI for MIBC prediction	Meta-analysis of imaging-based studies	AI models using CT, MRI, radiomics, and deep learning	CT AUC: 0.85; MRI AUC: 0.92; Radiomics AUC: 0.89; DL AUC: 0.91	High risk of bias; poor reporting and methodological quality (low CLAIM, RQS, PROBAST scores)
Suartz et al, 2024[51]	AI for predicting NAC response in MIBC	Systematic review and meta-analysis	ML models using CT, genomic, and pathologic data	Sensitivity: 62%; Specificity: 82%	Small number of eligible studies; moderate heterogeneity; lack of standardization
Lotan et al, 2024[52]	AI-powered prediction of BCG response in NMIBC	Multicenter diagnostic validation study	AI histologic assay on pathology slides (whole-slide images, feature extraction)	HR for progression: 3.87; HR for cystectomy: 3.35; HR for BCG unresponsiveness: 2.31	Retrospective design; external validation limited to participating centers only

Table 4 summarizes the key studies investigating the use of artificial intelligence in renal cancer, highlighting the type of AI models applied, study design, performance outcomes, and current limitations.

Many models have focused on differentiating benign from malignant kidney tumors, particularly distinguishing fat-poor angiomyolipomas from RCCs, achieving promising results.[64] *Fenstermaker et al* developed a CNN model trained on 3,000 normal and 12,168 RCC tissue samples from 42 patients (digital H&E-stained images from The Cancer Genome Atlas) to identify RCC in histopathologic specimens, differentiate subtypes (ccRCC, chrRCC, pRCC), and predict Fuhrman grades The model achieved 99.1% accuracy for distinguishing normal tissue from RCC, 97.5% for RCC subtype classification, and 98.4% for Fuhrman grade prediction, demonstrating the potential of AI in RCC diagnosis, subtyping, and grading.[60] Although the performance metrics were impressive, the model was developed using data from a limited number of patients and was not externally validated, which may reduce the robustness and generalizability of the findings.[60]

A noteworthy article in the field is the systematic review by *Zine-Eddine Khene et al*, which, by analyzing 20 studies, demonstrates the promising potential of machine learning and deep learning models in histological image analysis.[65] However, they also emphasize the challenges of clinical implementation, including methodological heterogeneity, lack of external validation, and the limited interpretability of AI algorithms.[65]

In addition to this, AI could be applied in RCC histopathology, such as *Alfredo Distante et al* examine in their systematic review enhancing the use of AI in diagnostic precision, tumor grading, and prognosis prediction while reducing interobserver variability and pathologists' workload.[66] So AI shows promise in automating histological assessments and integrating molecular data for improved patient stratification.[66] However, challenges remain regarding standardization, generalizability, and clinical implementation.[66]

Other AI-driven approaches explored, evaluate indirect markers of tumor aggressiveness, such as the SSIGN score (stage, size, grade, and necrosis), which predicts the progression of ccRCC following radical nephrectomy. For instance, *Choi et al* developed an AI algorithm to preoperatively predict low versus high SSIGN scores in ccRCC patients undergoing MRI, demonstrating a high AUC of 0.94.[61]

Kim et al used machine learning algorithms to predict RCC recurrence probabilities within 5- and 10-years post-nephrectomy, utilizing data from 6,849 patients in a Korean RCC database. They developed eight predictive models, achieving an AUC of 0.836 for 5-year recurrence and 0.784 for 10-year recurrence.[62] These results highlight the potential of machine learning to support clinical decision-making and enable more personalized post-surgical care.[62]

Renal clear cell carcinoma (RCC) is a complex disease with unpredictable patient outcomes. While targeted therapies have improved treatment, there remains a need for personalized treatment strategies.[67] In this regard Yu et al developed an AI-based predictive model for renal clear cell carcinoma (RCC) using the Unified Perceptual Parsing for Scene Understanding (UPerNet) algorithm to extract CT tumor marker features from a dataset of 267 patients, including 26 treated with targeted drug therapy.[63] Patients were categorized into two groups based on survival time (over or under 3

Table 4 Summary of Principal Articles Regarding AI Applied in Renal Cancer

Author and Year	Project Title	Study Type	AI Technique Used	Performance Metrics	Limitations
Fenstermaker et al, 2023[60]	CNN model for RCC diagnosis	Retrospective pathology study	CNN on histopathological images	Accuracy: 99.1%; Subtypes: 97.5%; Grading: 98.4%	Small dataset, no external validation
Choi et al, 2023[61]	AI prediction of SSIGN score	MRI-based predictive study	Machine learning on MRI features	AUC: 0.94	Only preoperative imaging used
Kim et al, 2023[62]	AI-based RCC recurrence prediction	Predictive modeling study	ML with clinical data	5-year AUC: 0.836; 10-year AUC: 0.784	Dataset limited to Korean population
Yu et al, 2024[63]	Predictive model for RCC treatment	Predictive model validation study	UPerNet on CT imaging	Accuracy: ~94% (survival prediction)	Small sample for patients on targeted therapy

years), and the model achieved high predictive accuracy, with rates of 93.66% for those surviving over 3 years and 94.14% for those under, highlighting the potential of AI to enhance clinical decision-making and support personalized treatment plans to improve patient outcomes and quality of life.[63]

Testicular Cancer

Testicular cancer is the most prevalent malignancy among adolescent and young adult men in the United States, with approximately 9,000 new cases annually.[68]

Table 5 outlines the most relevant studies addressing artificial intelligence in testicular cancer, with a focus on study design, AI methodology, and diagnostic or predictive performance.

To date, the application of AI in the management of this oncologic diseases remains limited and still in its early stages, with few studies n conducted on this topic. Among these, the work of *Moul et al* is particularly noteworthy. Moul and his team aimed to quantify primary tumor histologic factors and incorporate them into a neural network analysis to assess whether staging accuracy could be improved.[69] They first constructed a custom AI-model and then compared it with a commercial AI for staging testicular cancer using histologic factors.[69] The result obtained showed a superior performance of the custom AI than the commercial AI (92% vs 80% accuracy).[69]

The lymphovascular invasion is a key prognostic factor in testicular germ cell tumors, particularly in non-seminomatous stage 1 disease.[71]

The retrospective study of *Ghosh et al* aimed to develop and evaluate an AI algorithm capable of identifying suspicious areas of lymphovascular invasion in digital whole slide images.[70] A total of 184 H&E-stained slides from 19 patients (including seminoma and non-seminomatous cases) were annotated by expert pathologists. A deep learning classifier was then trained for automated segmentation of these regions.[70]

In a validation set of 118 slides from 10 patients, the model identified 34 suspicious areas, which were reviewed by three expert pathologists to reach a majority consensus. The algorithm achieved a precision of 0.68 for areas flagged as suspicious and 0.56 for confirmed lymphovascular invasion demonstrating the feasibility of an AI-assisted tool that highlights possible lymphovascular invasion for pathologists, who make the final diagnostic decision.[70]

A recent study led by *Lin-Jian Mo et al* developed AI-based predictive models (ANN, RF, SVM, and LR) to assess metastasis and treatment response in testicular cancer, using a risk score derived from the expression levels of 12 RNA-binding protein (RBP) genes, including GAPDH, APOBEC3G, ENO1, and HMGA1.[72] These models leverage transcriptomic data to predict lymph node metastasis, radiotherapy sensitivity, and chemotherapy efficacy—particularly distinguishing between responses to cisplatin and bleomycin—with the ANN model achieving the highest predictive accuracy.[72]

Table 5 Summary of Principal Articles Regarding AI Applied in Testicular Cancer

Author and Year	Project Title	Study Type	AI Technique Used	Performance Metrics	Limitations
Moul et al, 1997[69]	AI for staging testicular cancer	Comparative AI model evaluation	Custom neural network vs commercial AI	Accuracy: 92% (custom) vs 80% (commercial)	Very limited cohort; exploratory study
Ghosh et al, 2023[70]	AI detection of lymphovascular invasion	Retrospective histopathological study	Deep learning segmentation model	Precision: 0.68 (suspicious), 0.56 (confirmed)	Small sample size; lack of generalizability
International Germ Cell Cancer Collaborative Group, 1997[71]	Prognostic classification for metastatic germ cell tumors	Multinational prognostic cohort study	Not AI-based; multivariate clinical model (AFP, HCG, LDH, NPVM)	5-year survival: Good 91%, Intermediate 79%, Poor 48%	Traditional model; no use of AI; may not reflect recent advances in predictive modeling

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Artificial Intelligence Applied for Surgeons and Surgery

Robotic surgery is a key treatment approach for cancers of the urinary system and it offers precious advantages, including lower complication rates for patients compared to traditional open surgery, while enabling surgeons to perform procedures with greater precision.[11] Recently, efforts have been made to further enhance robotic surgery by integrating artificial intelligence (AI) to improve its capabilities.[73]

Augmented reality (AR) refers to systems that overlay digital information onto a real-world view, creating a blended environment. In surgery, this involves projecting preoperative or intraoperative imaging—such as CT, MRI, or ultrasound—onto the operative field, allowing real-time visualization of anatomical structures during laparoscopic or robotic procedures.[74] Recent advancements have enabled the integration of AR into urologic procedures, particularly in robot-assisted laparoscopic prostatectomy (RARP) and robotic or laparoscopic partial nephrectomy.[75,76] AR has primarily been employed intraoperatively to assist with tumor margin identification and surgical navigation. In addition, AR has been integrated with imaging techniques like SPECT and fluoroscopy to assist in percutaneous renal access and biopsy procedures.[77] Although AR-based technology shows considerable potential, current evidence does not clearly demonstrate a significant advantage over conventional techniques. Accurately aligning virtual models with anatomical structures that move or deform during surgery remains a major technical challenge for AR systems.[78] For AR to be clinically valuable, its tracking systems must deliver precise, real-time alignment of visual data with the operative field, particularly when dealing with flexible or mobile tissues.[79] The most accurate AR solutions often rely on complex multi-camera tracking systems, which substantially increase operational costs and limit widespread adoption.[80] The learning curve for radical prostatectomy demonstrates that higher surgical volumes lead to improved patient outcomes s, but relying solely on self-reported caseloads to assess performance is unreliable and inconsistent.[12] To address this limitation, various surgical assessment tools have been developed and validated to objectively measure surgical performance such as PACE (Prostatectomy Assessment and Competence Evaluation).[81] The PACE tool provides a structured, procedure-specific, and reliable method to objectively assess performance during robot-assisted radical prostatectomy, distinguishing between different expertise levels and offering structured feedback to support tailored training and improve surgical quality.[82]

The "dVLogger" (Intuitive Surgical) is an innovative data-recording device that captures APMs, including instrument motion tracking metrics and system events in Cartesian coordinates, along with synchronized surgical footage, directly from the da Vinci robotic system in real time during live surgical procedures.[83]

Hung et al conducted a study to evaluate the effectiveness of machine learning (ML) algorithms in assessing surgical performance throughout the RARP procedure and predicting patient outcomes, while also analyzing the importance of individual automated performance metrics (APMs). They proposed an ML-based method to objectively evaluate surgeons' performance by analyzing APMs, camera and instrument operation, and energy device usage, offering targeted feedback to both individual surgeons and academic institutions to improve performance evaluation and support efficient, ML-driven, and simulation-based training methods.[83]

Takeshita et al developed a CNN using a dataset of 1,040 images from intraoperative videos collected across three institutions (2019–2020), split into training and test sets at a 10:3 ratio, to accurately recognize the seminal vesicle and vas deferens (SV-VD) during robot-assisted radical prostatectomy (RARP), demonstrating its potential to enhance SV-VD recognition in posterior RARP, particularly benefiting novice surgeons.[84]

Natali Rodriguez Peñaranda et al investigated the role of AI in enhancing kidney cancer surgery by addressing challenges in surgical training, highlighting applications such as surgical workflow analysis, instrument annotation, tissue recognition, 3D reconstruction for preoperative planning and intraoperative guidance, and skill evaluation through procedural step identification and instrument tracking.[85] While noting that real-time tracking and accurate registration remain obstacles, yet emphasizing AI's potential to advance training through objective assessments, personalized feedback, and improved learning experiences.[85]

The role of AI in surgery is still evolving, with research in its early stages. However, progress is expected toward AI-enhanced and AI-assisted techniques, requiring the development of algorithms capable of recognizing and categorizing anatomical features and surgical instruments during operations.[86] Despite its growing presence, the use of AI and AR remains a relatively unfamiliar tool for many surgeons, contributing to hesitancy in clinical adoption.[87] Reducing the

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complexity of hardware configuration and eliminating time-consuming manual adjustments are key to making AR accessible for users across all levels of surgical expertise.[78]

Urologic-Oncology in Patient Care

AI has the potential to enhance patient care by providing clear explanations about surgical procedures, associated risks, and postoperative care.[88] Traditionally, patients have relied on search engines like Google for medical information.[89]

Hershenhouse et al conducted a study in which nine prostate cancer-related questions from Google Trends were classified into diagnosis, treatment, and follow-up. They used ChatGPT-3.5 to generate responses, which were simplified to enhance readability and ensure they were understandable at a sixth-grade reading level suitable for patients.[13] ChatGPT-generated responses were considered accurate by 71.7% to 94.3% of urologists and residents.[13] These responses were then resubmitted to ChatGPT with a request for further simplified summaries, which were rated accurate in 88.9% of cases and sufficient for decision-making in 88.9% of cases.[13] The goal was to create patient-friendly content that remained accurate and informative demonstrating the potential of ChatGPT as a tool for convenient patient education, despite not being explicitly designed for this purpose.[13] Additionally, its chatbot interface shows promise for generating accessible and easy-to-read summaries for the general public.[88] A key advantage of Large Language Models(LLMs) is their ability to communicate proficiently across various literacy levels and languages, making them powerful tools for engaging marginalized populations.[90]

However, since accuracy is not flawless, careful selection of information sources is essential to ensure reliability.[13]

Patients who have access to additional health information resources during the pre- and post-operative phases feel more prepared, more comfortable and experience lower 30-day readmission rates.[91]

Magdalena Görtz et al developed and evaluated the medical chatbot "prostate cancer communication assistant" (PROSCA), designed to provide information on early prostate cancer detection, prostate diseases, and treatment options.[92] Nine men with suspected Prostate Cancer (PCa) tested the chatbot, with 89% reporting increased knowledge, 78% finding it easy to use without assistance and all participants express expressing interest in reusing the chatbot in clinical practice.[92] PROSCA proved to be an innovative and effective tool for enhancing doctor-patient communication and improving health education.[92]

The implementation of machine learning algorithms in clinical practice depends on access to large volumes of patient data, raising significant concerns regarding privacy and data security. Furthermore, the ethical and legal implications of AI-assisted medical decision-making remain complex, with responsibility and accountability for AI-generated outcomes still poorly defined. While many of these challenges may be mitigated over time through technological advancements and improved data governance, further research is essential to ensure safe, transparent, and responsible integration of AI into healthcare.[92]

These concerns extend to patient-facing applications such as educational chatbots. While tools like ChatGPT and PROSCA can improve accessibility and engagement, they also raise important ethical and regulatory issues. For example, ChatGPT is not designed as a medical device and lacks formal validation processes, which raises concerns about misinformation, over-reliance, and patient autonomy. A global survey by *Eppler et al* revealed that over 50% of urologists encountered inaccuracies in LLM-generated outputs and most respondents supported the establishment of structured guidelines and oversight mechanisms.[93] Similarly, *Ganjavi et al* reported that only 24% of major publishers provided guidance on generative AI, with no structured policies available for clinical implementation.[94] These findings underscore the need for robust validation, ethical review, and regulatory frameworks to ensure responsible deployment of AI tools in patient education.

Although both PROSCA and ChatGPT use natural language processing to facilitate health communication, they differ in development, reliability, and clinical purpose[92] PROSCA was designed specifically for prostate cancer education, with medically validated content and structured dialogues, making it suitable for integration into patient counseling pathways.[92] ChatGPT, on the other hand, is a general-purpose language model trained on broad internet data without clinical oversight or domain-specific safeguards. Its outputs are generated probabilistically and may vary in accuracy or relevance. While ChatGPT may be useful for improving general health literacy, PROSCA offers a more dependable and clinically appropriate solution for patient-facing applications in urology.[92]

Implications of ChatGPT in Urologic Medical Writing

Generative AI (GAI) leverages large language models to produce original text or image-based responses to user inputs. Its popularity surged with the introduction of generative pretrained transformers (GPT), particularly with the launch of ChatGPT by OpenAI on November 30, 2022. Within just two months, ChatGPT amassed 100 million monthly users, marking it the fastest-adopted technology in history at that time.

John Mongan's team introduced CLAIM (Checklist for AI in Medical Imaging) to assist authors and reviewers of AI-related manuscripts in medical imaging.[15] This checklist has been expanded to encompass various AI applications, including classification, image reconstruction, text analysis, and workflow optimization,[15] and is updated on 2024.[95]

Eppler et al designed a prospective cross-sectional survey targeting 713 active members of the Young Academic Urologists Urotechnology Group of the European Association of Urology, the uroGPT HUB team (@uroGPT), and additional invited participants. The survey questions were collaboratively developed through an iterative process.[93] The primary goal was to assess urologists' familiarity with ChatGPT, its current applications in urology, potential future uses, ethical challenges, and healthcare regulation.[93] In their work approximately 53% of users reported encountering limitations when using ChatGPT or other LLMs in academic settings.[93] The most frequently cited challenges included inaccurate responses (44.7%), lack of specificity (42.4%), and inconsistent outputs (26.5%).[93] Additionally, there was broad opposition to the use of ChatGPT/LLM outputs in clinical care due to the lack of proper validation.[93] Among those utilizing ChatGPT/LLMs in urology, over half (52.4%) acknowledged inaccuracies in the generated outputs, while only 4.9% disagreed.[93] Furthermore, the majority of users (59%) indicated they would discontinue using ChatGPT if it were no longer offered for free.[93]

Moreover, a majority of participants (62.2%) acknowledge the presence of ethical concerns related to the use of ChatGPT in scientific and academic writing such as plagiarism (51.9%), artificial hallucinations (46.1%), and challenges in appropriately citing AI-generated content (30.5%).[93] Indeed, nearly 52% of respondents see ChatGPT as a threat to originality, while 48.7% express concerns about its impact on human creativity.[93]

Ganjavi et al conducted a study focusing on the 100 largest publishers, analyzing their policies to assess the scope and content of the guidance provided to authors regarding the use of generative artificial intelligence (GAI) in academic and scientific journals.[94] They noted that only 24% of publishers provided guidelines on the use of GAI in research, with most of these guidelines coming from publishers in the top quartile by journal count. Nearly 90% of the journals currently have such guidelines in place and 19 of them clarified that their GAI guidelines pertain solely to the writing process.[94] All publishers explicitly specified that AI cannot be listed as an author.[94] In conclusion, they observed a significant variability in the guidance regarding the use of GAI in academic research and scholarly writing reporting that none of the recommendations were developed through a structured, consensus-based guideline process.[94]

In addition in the work of *Eppler et al* participants expressed support for establishing clear guidelines (71.5%), for regular monitoring and auditing of AI systems (67.7%), and ethical and legal oversight (65.71%).[93]

This situation underscores the critical need for the development of unified, cross-disciplinary policies.[94]

From Hype to Hurdles: Current Limits and Future Paths for AI in Urologic Cancer

Despite the encouraging advances reported across the studies reviewed, several important limitations should be underlined. Much of the current evidence is based on retrospective, single-center, or pilot studies with relatively small patient cohorts, which limits both the external validity and the broader clinical applicability of the findings. Moreover, many of these studies rely exclusively on internal validation methods, without testing their models on independent datasets which is a critical step in demonstrating generalizability. Reported performance metrics such as accuracy, AUC, or precision are often not aligned with clinically meaningful outcomes and are seldom benchmarked against established diagnostic or therapeutic standards. Another key limitation concerns the geographic distribution of the literature: the majority of studies originate from high-income, Western academic institutions, raising questions about their relevance in more diverse or resource-limited settings. All these factors underscore the need for prospective, multicenter trials with standardized protocols and robust external validation to support the safe and effective integration of AI tools into real-world urologic oncology practice.

Conclusion

AI is emerging as a critical tool in urology, offering transformative potential in diagnosis, treatment, and surgical precision. By enhancing imaging analysis, enabling automated pathology workflows, and supporting robotic surgery, AI contributes to better patient outcomes and reduced healthcare burdens. Tools like aSPCNet, DeepSurv, PACE, Paige Prostate demonstrate the ability to improve diagnostic accuracy. Generative AI, including ChatGPT, further expands opportunities for patient education and communication, particularly for marginalized populations.

However, several challenges remain. Ethical concerns around transparency, accountability and bias are yet to be fully addressed. Regulatory frameworks often lag behind technological advancements and many AI models still lack robust clinical validation and external testing across diverse populations. Generalizability remains a key limitation due to variations in data sources, training methodologies and healthcare infrastructures.To allow responsible adoption, future efforts must prioritize data standardization, foster multicenter validation and establish clear ethical and legal guidelines. As AI technology continues to evolve, it will succeed in complement human expertise in urologic oncology provided its integration is guided by scientific rigor, inclusivity, and patient-centered principles.

Future studies should focus on real-world validation, cross-institutional collaborations, and rigorous evaluation of AI's clinical impact. As the technology continues to evolve, AI is poised to bridge the gap between human expertise and machine intelligence, reshaping urologic oncology toward more personalized, efficient, and equitable care.

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