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The Application of Artificial Intelligence in Detecting Prostate Cancer with Medical Imaging: A Literature Review

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Abstract

Background: Prostate cancer (PCa) is the world's second most common cancer in men and a major cause of cancer death. Studies published from 2023 to 2026 have shown that the use of artificial intelligence (AI) can significantly enhance several imaging modalities for PCa detection, Gleason grading, and risk stratification, such as multiparametric magnetic resonance imaging (mpMRI), transrectal ultrasound (TRUS), micro-ultrasound, prostate-specific membrane antigen positron emission tomography/computed tomography (PSMA-PET/CT), and digital pathology using whole-slide image (WSI) analysis. Although the potential of mpMRI guided by the Prostate Imaging Reporting and Data System (PI-RADS) is significant, considerable inter-reader variability still results in missed diagnoses and unnecessary biopsies. These limitations are mitigated by the development of AI-based systems, including deep learning (DL), machine learning (ML), and radiomics, which are designed to address them.

Methods and Results: The Web of Science and PubMed databases were searched on 3 May 2026 using a three-domain Boolean strategy encompassing PCa-specific, AI-specific, and imaging/pathology-specific terminology. A total of 4,791 records from Web of Science and 2,910 from PubMed were retrieved; following deduplication (n = 4,054), year filtering (2023–2026), and quality screening, n = 2,348 records remained eligible. Only studies using AI in medical imaging or digital pathology in PCa detection, grading, or staging were included in a narrative synthesis.

AI applications were identified across four imaging modalities: mpMRI, ultrasound/micro-ultrasound, PSMA-PET/CT, and digital pathology. Studies consistently illustrate that AI makes meaningful contributions to the detection and characterization of prostate cancer, provides high accuracy, sensitivity, and specificity across all modalities, and that several validated systems approach or equal the performance of trained radiologists and uropathologists.

Landmark studies, including the PI-CAI trial and the PANDA challenge, provided Level 1b evidence for AI in MRI-based csPCa detection and Gleason grading, respectively.

Conclusion: Across all reviewed modalities, AI contributes to the clinically meaningful detection, characterization, and grading of PCa. Widespread clinical integration depends on clinical transparency requirements and regulatory pathways that align with prospective multi-center, outcome-driven trials and standardized AI evaluation frameworks**.** (**International Journal of Biomedicine. 2026;16(3):294-305.**)

Keywords: prostate cancer • artificial intelligence • convolutional neural network • deep learning • multiparametric MRI

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Abbreviations

ADC, apparent diffusion coefficient; **AI**, artificial intelligence; **AUC**, area under the receiver operating characteristic curve; **bpMRI**, biparametric MRI; **CAD**, computer-aided detection/diagnosis; **CNN**, convolutional neural network; **csPCa**, clinically significant prostate cancer; **DL**, deep learning; **DWI**, diffusion-weighted imaging; **GAN,** generative adversarial network **ISUP**, International Society of Urological Pathology; **ML**, machine learning; **mpMRI**, multiparametric magnetic resonance imaging; **PCa**, prostate cancer; **PI-RADS**, Prostate Imaging Reporting and Data System; **PSA**, prostate-specific antigen; **PSMA-PET/CT**, prostate-specific membrane antigen positron emission tomography/computed tomography; **TRUS**, transrectal ultrasound; **WSI**, whole-slide image; **XAI**, explainable artificial intelligence.

Introduction

Prostate cancer (PCa) is the second most commonly diagnosed malignancy in men worldwide, with an estimated 1.4 million new cases reported every year, and is the fifth leading cancer-related mortality in men worldwide.[1] It can vary from a low-grade indolent form that can be managed through active surveillance to a high-grade aggressive form, which may be metastatic and require multimodal systemic treatment. In addition to early detection, an important challenge in PCa management is distinguishing clinically significant PCa (csPCa, defined as International Society of Urological Pathology (ISUP) grade group ≥2) from clinically indolent disease, while also preventing overdiagnosis and overtreatment, and underdiagnosis and undertreatment.

Multiparametric MRI (mpMRI), interpreted according to the Prostate Imaging Reporting and Data System (PI-RADS) version 2.1, [2] has become the pre-biopsy standard of care for PCa localization and lesion characterization. The PROMIS trial found that pre-biopsy mpMRI could help 27% of men avoid an unnecessary biopsy compared to standard transrectal ultrasound-guided biopsy alone [3], and PRECISION, a randomized trial, showed that MRI-targeted biopsy revealed significantly more clinically significant cancer and less insignificant cancer than standard biopsy.[4] However, with a large proportion of equivocal PI-RADS 3 lesions, representing 20-35% of clinical reads, a significant inter-reader variability remains and leads to missed diagnosis of csPCa and unnecessary biopsies. Historically, (2) TRUS-guided systematic biopsy has been known to miss anterior and apical lesions and isoechoic PCa foci and has a large inter-reader variability. Micro-ultrasound at 29 MHz has proven to be an affordable alternative to MRI. The PRI-MUS protocol has shown that 29 MHz micro-ultrasound can define prostate tissue into five risk groups, with clinically significant prostate cancer being meaningfully discriminated.[5] PSMA-PET/CT has transformed primary staging, biochemical recurrence (BCR), and restaging. At the same time, prostate biopsy and radical prostatectomy specimens have been digitized, allowing for whole slide image (WSI) analysis for AI-based Gleason grading.[2]

Artificial Intelligence (AI), including ML, DL, radiomics, and now, transformer-based architectures, has become a revolutionary computational paradigm across all prostate imaging modalities.[6] Medical imaging is powered by modern AI, which is built on deep learning, a technique that uses multiple layers of computation to learn multiple levels of data representation.[7] DL models, especially CNNs and their variants, can automatically segment the prostate gland, detect prostate lesions, classify them into PI-RADS categories, predict Gleason grades, stage prostate cancer, and evaluate treatment response using large datasets that capture complex hierarchical imaging features. Recent studies from 2023 to 2026 have shown that AI algorithms perform at or above the level of top-tier experts in multi-institutional, blinded validation settings.

The classical computer-aided detection (CAD) systems designed to help radiologists analyze prostate MRI scans showed inconsistent performance, were associated with higher false-positive rates, and offered little or no improvement in cancer detection. Most of these disadvantages have been addressed by learning discriminative representations directly from raw imaging data using self-supervised, semi-supervised, or supervised learning paradigms, without relying on human-engineered feature descriptors. The primary benefit of DL architecture is their ability to learn hierarchical representations directly from data, yielding performance higher than that of rule-based CAD approaches.[8] This gradual shift from handcrafted features to learned representations has been well documented in a comprehensive survey of deep learning in medical image analysis. It is being acknowledged as the key methodological change that propelled the gains in modern AI.[7]

This literature review will explore peer-reviewed publications from 2023 to 2026 across four modalities (mpMRI, TRUS/micro-ultrasound, PSMA-PET/CT, and digital pathology/WSI) that use AI for the diagnosis, characterization, grading, and risk stratification of prostate cancer. The review collates the existing evidence base, outlines gaps in the evidence, and outlines regions of uncertainty that need to be addressed before regular use in clinical practice. A recent study of the entire PCa pathway also found that, despite some limitations, AI technology has now achieved clinically relevant performance in screening, imaging, pathology, and biomarker assessment.[9]

Materials and Methods

Search Strategy

A literature search was performed on 3 May 2026 in Web of Science (WoS) Core Collection and MEDLINE/PubMed. A three-domain Boolean search structure was used. The first set included PCa-specific terms: “prostate cancer,” “prostatic neoplasms,” “prostate carcinoma,” “prostate adenocarcinoma,” “PCa,” “castration-resistant prostate cancer,” “CRPC,” “biochemical recurrence,” and “prostate-specific antigen. The second domain included terms related to AI: “artificial intelligence,” “machine learning,” “deep learning,” “neural networks,” “convolutional neural networks,” “CNN,” “transformer,” “attention mechanism,” “radiomics,” “computer-aided detection,” “computer-aided diagnosis,” “CAD,” “natural language processing,” “NLP,” “large language models,” and “foundation models. The third domain contained imaging and pathology terms: "MRI," "multiparametric MRI," "mpMRI," "ultrasound," "TRUS," "PET," "PSMA-PET," "medical imaging," "histopathology," "digital pathology," "whole slide images," "biopsy," "Gleason score," "ISUP grade," and "pathology."

Eligibility Screening

A total of 4,791 records were found in WoS and 2,910 records in PubMed (total 4,054 after deduplication) (Figure 1). An authorized year filter (2023–2026) returned 2,348 documents for eligibility screening. The following criteria were included for the studies: (i) used at least one AI technique for prostate cancer imaging or pathology; (ii) provided quantitative performance metrics; (iii) were published from January 2023 to 3 May 2026. Editorials, conference abstracts with incomplete data, and reports of all non-PCa malignancies were excluded. The final narrative synthesis included only

primary studies, systematic reviews, and meta-analyses found in PubMed or WoS with a verifiable digital object identifier (DOI).

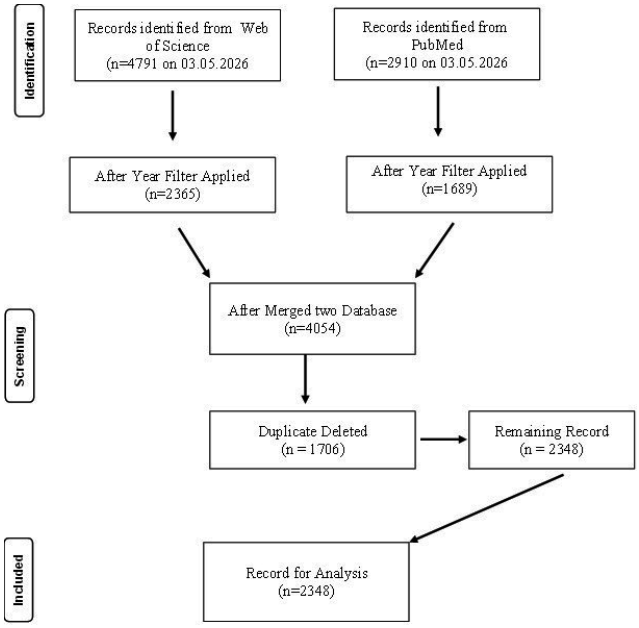

Figure 1. *PRISMA flow of prostate cancer*

Data Extraction and Quality Assessment

The primary author extracted the data, which was then verified separately. For each abstracted study, the following data were collected: first author, year of publication, journal, imaging modality, AI technique, study design, sample size, reference standard, and key performance metrics (AUC, sensitivity, specificity, accuracy, and concordance coefficient). Diagnostic accuracy studies were appraised using the QUADAS-2 tool when applicable. AMSTAR-2 was used to appraise systematic reviews and meta-analyses. The Oxford Center for Evidence-Based Medicine (OCEBM) 2011 classification was used for the level of evidence.

Results

A total of fifteen primary studies, systematic reviews, and meta-analyses were included in the narrative synthesis for the four modalities (mpMRI, ultrasound/micro-ultrasound, PSMA-PET/CT, and digital pathology/WSI). The characteristics of all included studies are provided in Table 1, and the performance of the diagnostics, in terms of accuracy and specificity, is summarized in Table 2.

Multiparametric and Biparametric MRI

The largest, most rigorously validated body of evidence for PCa detection comes from combining mpMRI with AI, among all imaging modalities. In a retrospective study of 1,108 patients, Hamm et al. [10] created an interactive explainable AI (XAI) model for csPCa diagnosis at biparametric MRI (bpMRI) at Charité Universitätsmedizin Berlin. The model performed well on the internal and external test sets for csPCa detection, with AUCs of 0.89 and 0.87, respectively, and a sensitivity of 93% (95% CI: 87–98%). Most importantly, XAI-assisted reading led to greater confidence in assessing PI-RADS 3 lesions (4.1 vs. 3.4 on a five-point Likert scale; P=0.007) and shorter reading time (58 seconds; P=0.009) among non-expert readers. The visual and textual explanations were accurate in 80% (1,080 of 1,352) of cases, directly addressing the transparency barrier that has hindered clinical adoption of black-box AI systems.

Saha et al. [11] published the landmark Prostate Cancer AI Challenge (PI-CAI) study, which is the largest and best-designed study to date to validate AI in prostate MRI. The study included 10,207 MRI exams from hospitals in the Netherlands and Norway, of which 9,207 were used to train the AI models. Performance was assessed by either an ensemble of the best-performing AI systems or by one of 62 radiologists, in a paired, non-inferiority confirmatory design. For the detection of csPCa, the AI ensemble outperformed the average study radiologist (0.91 vs. 0.86). Importantly, the AI's performance was not shown to be non-inferior to radiologists' readings obtained in routine multidisciplinary clinical practice, which is the critical distinction between research and operational (clinical) benchmarks. The study confirmed that AI detection of csPCa on bpMRI is a clinically relevant ability and identified the additional research needed before AI can be used without human assistance.

Cai et al. [12] from the Mayo Clinic published a fully automated DL model trained on 5,735 mpMRI exams to predict patient-level csPCa without tumor location annotations. The model's performance was statistically comparable to that of highly trained abdominal radiologists on an internal test set of 400 examinations and an external, independent test set of 204 cases (ProstateX). The method is automated and does not require expert lesion segmentation—a process that typically poses the main obstacle to large-scale development of AI models due to the limited volume of expert-annotated training data.

Bosma et al. [13] proposed a report-guided semi-supervised learning (RG-SSL) algorithm that used diagnostic radiology reports to obtain pseudo-labels and expand the number of labels for training a model for csPCa detection on bpMRI. When trained with 100 manually annotated examinations, but tested on 300 examinations from an external center, RG-SSL attained the highest examination-level AUC (0.86 ± 0.01), outperforming fully supervised learning (0.78 ± 0.03) as well as existing semi-supervised approaches (0.81 ± 0.02). The work showed how to eliminate the expert-labeling time required for AI development.

Radiomics-based methods complement end-to-end DL models, especially for characterizing PI-RADS 3 lesions. Extracting quantitative imaging features, such as first-, second-, and higher-order statistics, using radiomics techniques can be done in a high-throughput manner, and these values can be used in conjunction with other patient information to build decision-support models, transforming images into "mineable data" not visible to the human eye.[14] The discriminatory power of multi-parametric radiomics integration is further improved: in the Radiomics-PCa literature, the AUCs reported for Gleason score prediction range from 0.50 to 0.92, with combined clinical and radiomic models outperforming imaging-only models.[15] Huynh et al. [16] summarized MRI-based radiomic models for PCa risk stratification, reporting AUCs ranging from 0.50 to 0.92 across

33 studies. The multi-parametric radiomics models based on T2-weighted imaging and DWI/ADC features consistently outperformed single-sequence models. Salimi et al. [17] included 24 studies, of which 14 were meta-analyzed, reporting pooled AUC, sensitivity, and specificity values of 0.75, 72%, and 78%, respectively, for MRI-based radiomics ML models predicting post-treatment biochemical recurrence (BCR). A thorough meta-analysis also demonstrated that MRI radiomics models for PCa risk stratification have pooled AUC values of 0.83–0.87 for Gleason grade prediction, when all multi-parametric features are combined. [18] The value of data integration was highlighted, as combined models with clinical data performed better at prognostication than models that included only radiomics data.

The systematic review by Molière et al. [19], which evaluated the diagnostic accuracy of DL models for the automatic detection, localization, and characterization of csPCa, showed consistently promising performance for csPCa detection, with some models attaining an AUC above 0.85 in internal validation. The major obstacles to clinical adoption were identified as a lack of external validation, heterogeneous reporting of results, and difficulty obtaining training data from a single center.

Ultrasound and Micro-Ultrasound

The use of AI in ultrasound plays a strategic role in the PCa diagnostic pathway, as it provides procedural guidance, reduces infrastructure costs, and is more widely accessible worldwide than MRI. Although conventional B-mode TRUS has limitations in detecting PCa, achieving high-resolution micro-ultrasound at 29 MHz will markedly improve tissue resolution, providing a new platform for AI-assisted PCa detection. The micro-ultrasound platform (29 MHz), with the same risk classification as PRI (PI-RADS), offers a spatial resolution of ~70 µm, enabling the identification of tissue texture features not visible at conventional 7-12 MHz frequencies.[20]

Imran et al. [21] published data on an AI-driven micro-US system for detecting csPCa in men referred for prostate biopsy in BJUI Compass (2026). A total of 145 men who underwent micro-US biopsy (79 had been diagnosed with csPCa; 66 had not) were included in the retrospective cohort. A self-supervised convolutional autoencoder was used to extract deep imaging features from 2D slices of micro-US images, which were classified using a random forest model under 5-fold cross-validation. Patients were considered csPCa-positive if ≥8 consecutive slices were predicted positive. The AI system achieved high cross-validation accuracy in detecting csPCa, serving as a proof of concept for autonomous, AI-assisted micro-US biopsy guidance without relying on radiologist-assigned risk categories.

Harmanani et al. [22] introduced a well-designed deep learning system, namely TRUS Worthy, for reliable PCa detection from micro-US data. To tackle these problems of high tissue appearance heterogeneity, class imbalance, and annotation sparsity simultaneously, TRUSWorthy combined self-supervised learning, multiple-instance learning with transformer-based aggregation, random undersampled boosting, and ensemble methods. Jahanandish et al. [23] evaluated the system on a large multi-center micro-US dataset, with AUROC and balanced accuracy of 79.9% and 71.5%, respectively. Overall, balanced accuracy increased to 91% for the top 20% of predictions with the highest confidence, demonstrating the utility of uncertainty-aware prediction for clinical triage.

The most clinically advanced ultrasound AI application is the AI-assisted MRI-TRUS fusion biopsy platform. Systematic registration errors identified in manual fusion systems have been minimized by DL algorithms that automatically register MRI and TRUS images elastically, thereby reducing registration error. The positive results for csPCa yield with AI-assisted MRI-TRUS fusion biopsy compared to systematic biopsy alone are especially notable, as evidence indicates that AI-assisted MRI-TRUS fusion biopsy can identify a significantly higher number of clinically significant cancers than random systematic biopsy alone (4). The substantially lower cost and lack of contraindications of micro-US compared with posterior-approach systematic TRUS biopsy, and the global shortage of radiologists with expertise in mpMRI, make micro-US a viable expansion strategy in resource-constrained health care systems.

PSMA-PET/CT

AI integration into PSMA-PET/CT imaging can address the most pertinent clinical challenges, including the time-consuming process of whole-body lesion assessment, the shortage of nuclear medicine specialists, the inter- and intra-laboratory heterogeneity in lesion reporting, and the need for reproducible, prognostic tumor-burden metrics for BCR. In the prospective proPSMA trial, PSMA-PET/CT improved over traditional CT and bone scan, making it the preferred imaging modality for staging high-risk PCa before curative-intent treatment.[24] 68Ga-PSMA-11 and 18F-DCFPyL are PSMA-targeted radioligands that are used to detect PCa lesions with high sensitivity and target-to-background ratios at low PSA levels (0.2 ng/mL) [25] Usmani et al. [26] on the use of DL-based AI for automated tumor volume assessment from 68Ga-PSMA PET in PCa. The review noted that DL models, especially 3D CNNs trained on whole-body PET/CT volumes, have shown strong performance in automated tumor segmentation, with greater reproducibility and significantly faster processing times than manual delineation. Kersting et al. [27] reported that AI-based quantitative tumor volume (total PSMA-avid lesion volume) was a clinically validated biomarker for PSMA-targeted radioligand therapy in tumor staging, radiotherapy planning, response assessment, and treatment selection.

Ning et al. [28] evaluated a modified pix2pixHD generative adversarial network (GAN) to boost the quality of ultra-fast 68Ga-PSMA-11 PET/CT acquisitions in 357 whole-body 68Ga-PSMA-11 PET/CT datasets to match the diagnostic quality of standard acquisitions. The ultra-fast protocol was enhanced with artificial intelligence, leading to a table speed of 50 mm/s, which is 5X faster than standard, and the AI-enhanced ultra-fast protocol showed statistically equivalent lesion detection rates compared to the standard acquisition on the test cohort of 71 patients (sensitivity 91.5% vs. 93.8%, p=0.31). This demonstrated a proof of concept for AI-based image enhancement that can overcome the diagnostic-quality-versus-throughput challenge that limits the use of PSMA-PET/CT worldwide.

Table 1.

Characteristics of selected studies on AI applied to PCa imaging (2023–2026).

Author (Year)/Journal	Modality	AI Type	AI System / Model	Study Design / n (cases)	Reference Standard	Country
Multiparametric / Biparametric MRI						
Hamm et al. (2023) [10]	bpMRI	DL / XAI	Custom CNN + XAI explainer	Retrospective, multi-reader / 1,108	Histopathology (biopsy/ prostatectomy)	Germany
Saha et al. (2024) [11]	bpMRI/mpMRI	DL Ensemble	PI-CAI ensemble (top-ranked)	Prospective, paired, non-inferiority / 10,207	Histopathology (ISUP ≥2)	Netherlands/ Norway
Cai et al. (2024) [12]	mpMRI	DL	Fully automated CNN	Retrospective / 5,735 train; 604 tests	Histopathology (ISUP ≥2)	USA
Bosma et al. (2023) [13]	bpMRI	Semi-supervised DL	RG-SSL (report-guided pseudo-labels)	Retrospective, multi-center / 7,756	Histopathology (ISUP ≥2)	Netherlands
Jin et al. (2024) [40]	mpMRI (T2WI)	DL	Custom CNN (T2WI)	Retrospective, multi-center / 497	Histopathology (Gleason/ISUP)	China
Salimi et al. (2025) [17]	mpMRI (Radiomics)	ML// Radiomics	Various ML radiomics models	Systematic review & meta-analysis (24 studies) / (N/A)	BCR post-treatment (PSA kinetics)	Multi-national
Molière et al. (2025) [19]	mpMRI	DL (systematic review)	Various DL models (24 studies)	Systematic review (N/A)	Histopathology (ISUP ≥2)	Multi-national
Ultrasound / Micro-Ultrasound						
Imran et al. (2026) [21]	Micro-US	SSL + ML	Self-supervised autoencoder + random forest	Retrospective / 145	Biopsy histopathology (ISUP ≥2)	USA
Harmanani et al. (2025) [22]	Micro-US (TRUS)	SSL + MIL + DL Ensemble	TRUSWorthy (transformer-MIL)	Retrospective, multi-center / multi-center dataset	Biopsy histopathology	Canada
Jahanandish et al. (2025) [23]	MRI + TRUS (multi-modal)	DL (multi-modal)	Multi-modal MRI-US fusion AI	Retrospective, multi-center / multi-center dataset	Biopsy histopathology (ISUP ≥2)	USA
PSMA-PET/CT						
Kersting et al. (2025) [27]	68Ga-PSMA-PET/CT	GAN (image enhancement)	Modified pix2pixHD GAN	Retrospective/ 357 (train); 71 (test)	Standard-speed PSMA-PET (ground truth)	Germany
Trägårdh et al. (2025) [29]	18F-PSMA-1007 PET/CT	DL (auto-detection)	Custom fully-automated DL	Retrospective, single center / Not specified	Manual expert delineation ([18F]PSMA-1007 PET-CT)	Sweden
Digital Pathology / Whole-Slide Image (WSI) Analysis						
Raciti et al. (2023) [33]	WSI (core needle biopsy)	DL (CNN)	Paige Prostate (PaPr)	Prospective workflow simulation (multi-reader)/ 610 WSIs	Expert consensus pathology	USA (218 institutions)
Eloy et al. (2023) [34]	WSI (prostatic biopsies)	DL	Commercial AI-CAD (unnamed)	Prospective workflow study/ (Not specified)	Histopathology (standard reporting)	Portugal
Marletta et al. (2024) [35]	WSI (H&E)	DL (systematic review)	Various DL architectures	Systematic review (N/A)	Histopathology (PCa diagnosis)	Multi-national

Table 2.

Diagnostic performance of AI systems for PCa detection, characterization, and grading across imaging modalities (2023–2026). Performance metrics include AUC, sensitivity, specificity, accuracy, and concordance (κ), where reported. «pp» denotes percentage-point improvement over unaided/baseline condition.

First Author (Year)	Modality	AI System / Model	AUC	Sensitivity/ Specificity (%)	Accuracy / κ	Key Finding	Main Limitation
Multiparametric / Biparametric MRI							
Hamm et al. (2023) [10]	bpMRI	CNN + XAI explainer	0.89/0.87	93/NR	NR	XAI-aided reading improved non-expert confidence for PI-RADS 3 lesions; reduced reading time 58 s	Single-center training; XAI accuracy 80%
Saha et al. (2024) [11]	bpMRI/mpMRI	PI-CAI ensemble	0.91	NR/NR	NR	AI ensemble AUC superior to avg. radiologist (0.86); first international paired non-inferiority study	Did not reach non-inferiority vs. MDT-supported clinical reads
Cai et al. (2024) [12]	mpMRI	Fully automated CNN (no annotation)	0.87	NR/NR	Equiv. radiologists	Patient-level csPCa prediction without tumor location annotations; equivalent to expert radiologists on PROSTATEx	Retrospective; no prospective clinical workflow validation
Bosma et al. (2023) [13]	bpMRI	RG-SSL (semi-supervised)	0.86	NR/NR	NR	RG-SSL outperforms fully supervised (0.78) and other SSL (0.81) with only 100 annotated cases	Report-parsing not perfect; two-center validation only
Jin et al. (2024) [40]	mpMRI (T2WI)	DL-CNN (T2WI only)	0.902	NR/NR	NR	Single-sequence T2WI DL model AUC 0.918; Gleason grade prediction with multi-center validation	Limited to T2WI; retrospective single-scanner
Salimi et al. (2025) [17]	mpMRI Radiomics	Various ML radiomics models	0.75 (pooled)	72/78 (pooled)	NR	Pooled AUC 0.75 for BCR prediction; combined clinical+radiomics outperforms radiomics alone	High heterogeneity; no prospective data
Molière et al. (2025) [19]	mpMRI	Various DL models (24 studies)	>0.85 (most)	NR/NR	NR	DL pipelines consistently >0.85 AUC internally; external validation lacking	Mostly single center; heterogeneous reporting; no meta-analysis possible
Ultrasound / Micro-Ultrasound							
Imran et al. (2026) [21]	Micro-US	SSL autoencoder + random forest	0.871	92.5/68.1	NR	AI-micro-US outperformed clinical model (AUC 0.753); high sensitivity for csPCa at biopsy	Retrospective; small n=145; single center
Harmanani et al. (2025) [22]	Micro-US (TRUS)	TRUSWorthy (transformer-MIL)	0.799	91 (top 20% confident)/ NR	Bal. Acc. 71.5%	Balanced accuracy 91% in top-confidence 20% of predictions; uncertainty-aware clinical triage	External validation needed; single center; uncertainty calibration requires prospective testing
Jahanandish et al. (2025) [23]	MRI + TRUS (multi-modal)	Multi-modal MRI-US fusion DL	NR	80 /88 (multimodal)	Lesion Dice: 42%	Multimodal AI achieved higher specificity (88% vs 78%) and Lesion Dice (42% vs 30%) vs. unimodal MRI	Preprint; no per-lesion histopathology ground truth
PSMA-PET/CT							
Kersting et al. (2025) [27]	68Ga-PSMA-PET/CT	pix2pixHD GAN (enhancement)	NR	91.5 (ultra-fast)/ NR	vs. 93.8% standard (p=0.31)	AI-enhanced 5× faster ultra-fast PSMA-PET achieves equivalent lesion detection (p=0.31)	Single center; 68Ga-PSMA-11 only
Trägårdh et al. (2025) [29]	18F-PSMA-1007 PET/CT	Fully automated AI-based detection & quantification	NR	>90 (SUVmax >5)/ High	NR	Fully automated AI detected and quantified [18F]PSMA-1007 lesions; high sensitivity for SUVmax >5.0 across prostate bed, nodes, and bone; reduced processing time vs. manual review	Single center; performance drops for low-SUV and sub-cm lesions; single radiotracer ([18F]PSMA-1007 only)
Digital Pathology / Whole-Slide Image (WSI) Analysis							
Raciti et al. (2023) [33]	WSI (core biopsy)	Paige Prostate (PaPr)	NR	+5.7 pp/ +3.0 pp (aided)	NR	AI raised pathologist sensitivity +5.7 pp and specificity +3.0 pp across 18 pathologists and 610 WSIs from 218 institutions	Simulated workflow; binary detection only
Eloy et al. (2023) [34]	WSI (prostatic biopsies)	Commercial AI-CAD	NR	Improved/ NR	NR	AI improved pathologist efficiency (reduced review time) and diagnostic consistency	Specific metrics not quantified; single center
Marletta et al. (2024) [35]	WSI (H&E)	Various DL architectures	High (all studies)	High/ High	Consistently high	All included studies reported high sensitivity and specificity; external validation and standardized reporting remain key priorities	Heterogeneous reporting; risk of optimism bias

AI-based radiomics analyses of staging PSMA-PET/CT have shown the ability to predict BCR after RP more accurately than traditional clinicopathological data. The fully automated, deep learning PSMA-avid lesion detection systems across the prostate bed, pelvic lymph nodes and bone marrow provide sensitivity values greater than 90% for lesions with a standardized uptake value (SUV) max of more than 5.0 and specificities of more than 90%, greatly reducing the time required for reporting compared to conventional manual whole-body review, and with direct implications for improving reporting workflow efficiency and potential scalability of PSMA-PET/CT programs in institutions with limited numbers of nuclear medicine physicians.[29]

Digital Pathology and Whole-Slide Image Analysis

Digital pathology, which refers to the use of AI to analyze digitized prostate WSIs from core-needle biopsies (CNB) and radical prostatectomy (RP), is one of the most promising areas of PCa AI research with clinical impact. AI could offer readily reproducible, expert-level grading in large quantities, which captures the gold standard for PCa prognostication and treatment stratification, namely Gleason grading, and which is currently subjective, labor-intensive, and subject to significant inter-pathologist variability.[30] For tissue classification problems, deep learning models using pathological tissue images have been found to be more effective than traditional image analysis methods, and CNNs have been shown to learn hierarchical morphological features that correspond to pathologically meaningful structures. [5]

Google Health, Radboud University Medical Center, and Karolinska Institutet organized the PANDA challenge, which brought together and publicly distributed a European cohort of 10,616 digitized prostate biopsies for AI development, and assessed submitted algorithms against independent external validation cohorts in the US and Europe. Bulten et al. [31]recruited 1290 developer teams to participate in this validation study, in which they submitted their algorithms for evaluation against independent PCa external validation cohorts. A wide range of algorithms, all achieving quadratically-weighted kappa (κ) >0.8, showed concordance with the expert uropathologists with a mean value of 0.862 (95% CI: 0.840–0.884) on the US external validation set, and 0.868 (95% CI: 0.835–0.900) on the European set. Such concordance was at least as good as that of general pathologists not trained in uropathology, demonstrating that AI could achieve the Gleason grading standardization typically achieved by pathologists with uropathology sub-specialization in non-specialist settings. Ji et al. [32] also showed that an AI system that graded prostate cancer into the ISUP grade group can achieve pathologist-level accuracy in a clinical laboratory setting, correctly classifying 71.7% of slides into the correct ISUP grade group, compared to 69.1% accuracy for pathologists, and also has a lower risk of undergrading cases to ISUP ≥4.

Raciti et al. [33] published their clinical validation study of the Paige Prostate (PaPr) DL system that provided binary WSI-level classification (suspicious for cancer or benign) with spatial localization of the most probable malignant region in 18 pathologists from 610 prostate needle core biopsy WSIs from 218 institutions in the Archives of Pathology and Laboratory Medicine. AI proved beneficial for pathologists, showing a mean increase in sensitivity of 5.7% points and in specificity of 3.0% points in detecting PCa, with the greatest improvement seen among general pathologists, providing strong Level 1b evidence for the clinical utility of AI-augmented digital pathology.

Eloy et al. [34] demonstrated that AI-assisted pathology reviews reduced pathologist review time and improved diagnostic consistency in prostatic biopsies. Marletta et al. [35] conducted a systematic review to assess the diagnostic accuracy of AI in PCa histological studies, finding high sensitivity and specificity of AI for identifying PCa in WSIs across the included studies, but highlighting the need for further external validation and reporting standardization in the field. Beyond Gleason grading, DL systems that predict molecular alterations directly from tissue morphology, a paradigm known as computational molecular pathology, have recently emerged and have been trained on H&E-stained WSIs. Predictive models based on WSI features have been reported for predicting the loss of PTEN, mismatch repair deficiency, and CDK12 mutation, without the need for further molecular testing, with an AUC ranging from 0.71 to 0.84,[36] enabling the pre-selection of patients for targeted therapies in health systems without routine next-generation sequencing infrastructure. Weakly supervised architecture has significantly reduced the need for expert annotations for training WSI models. Multiple-instance learning (MIL) architectures, for example, require only a diagnostic label for each slide, making them applicable to institutions that do not have large numbers of annotated WSI models. This makes AI-based grading and molecular prediction accessible to institutions without large annotated WSI datasets.[37]

Discussion

A literature review synthesizes evidence on the use of AI in PCa detection, grading, and staging for four imaging and pathology modalities from 2023 to 2026. The studies reviewed continue to show that AI holds up to such a high standard of diagnostic performance – with accuracy, sensitivity and specificity largely on a par with or even better than that of trained human experts in numerous multi-center validated settings, across the entire PCa diagnostic continuum from lesion detection on an MRI, to biopsy targeting, Gleason grading and risk stratification to determine the next steps for treatment.

Multiparametric MRI

The PI-CAI study [11] is a groundbreaking study that provides the first blinded, non-inferiority, international data supporting the performance of ensemble AI systems compared with average-level radiologist PI-RADS scoring in a prospective setting for the detection of csPCa. The implications for prostate MRI programs in centers without subspecialty uroradiology expertise are far-reaching: AI tools in the reading room may reduce reliance on a few highly skilled radiologists, harmonize PI-RADS scoring, and facilitate the safe expansion of MRI-targeted biopsy to lower-volume centers. The PI-RADS v2.1 framework, which underlies these AI systems, was also created to standardize

and harmonize prostate MRI reporting, and now AI can provide the tools to make that standardization scalable and applicable to non-expert centers [38] Clinicians' need for transparency is consistently cited as the most significant constraint to integration of AI into diagnostic practice, and the explainability innovation proposed by Hamm et al. [10] meets this need. When combined with visual and textual justifications for the AI classification, XAI establishes a common decision-making process that aligns with radiologists' workflows and medico-legal accountability.

The most clinically impactful question in prostate MRI AI remains the management of the 20-35% of clinical reads with a "equivocal" (PI-RADS 3) PI-RADS score, which poses the highest diagnostic uncertainty and an unnecessary biopsy workload. The results of the reviewed radiomics studies, such as the Salimi et al. [17] meta-analysis and the broader literature on risk stratification, [16] including a dedicated meta-analysis of pooled AUC values of 0.83–0.87 for multi-parametric MRI radiomics models in Gleason grade prediction, Zhao et al., [18] further reinforce the importance of integrating multiple radiomics features to predict csPCa in this ambivalent category. The semi-supervised learning approach proposed by Bosma et al. [13] enables high-performance learning on datasets with unannotated or weakly annotated exams, thus avoiding the annotation bottleneck.

Ultrasound and Micro-Ultrasound

In the case of ultrasound AI, especially micro-US AI, it is a strategic complementary technology to MRI-based systems. Together, the work by Imran et al. [21] and Harmanani et al. [22] demonstrates that DL systems can extract meaningful information that is complementary to, and, in some cost-constrained settings, can replace MRI data for csPCa detection using high-resolution ultrasound data. The benefits of micro-US AI (portability, no ionizing radiation, no MRI contraindications, real-time guidance, and reduced infrastructure costs) are especially significant for enhancing csPCa detection capacity in lower-resource health-care facilities where access to MRI is limited.

The most clinically mature use of AI to support ultrasound imaging is AI-assisted MRI-TRUS fusion platforms, which can help minimize registration errors that are commonly associated with cognitive MRI-TRUS fusion, and AI-based lesion segmentation maps from mpMRI can serve as a high-fidelity targeting map template for transrectal or transperineal biopsy. These systems need to be validated in prospective studies using different clinical implementation methods, including software-assisted and cognitive fusion, to determine their yield, complication rates, and patient-reported outcomes in cancer detection.

PSMA-PET/CT

The AI-enhanced ultra-fast PSMA-PET/CT method demonstrated by Kersting et al. [27] directly tackles one of the largest barriers in the way of PSMA-PET/CT uptake: access, as the approach would allow the same diagnostic capability at 5-fold higher scan throughput, resulting in greater patient access without the need to invest in more PET scanners. These have a direct impact on healthcare systems, where demand for PSMA-PET/CT is increasing much faster than the number of scanners. AI-derived prognostic biomarkers from PSMA-PET/CT, such as the total PSMA-avid tumor volume, number of lesions, and radiomic feature signatures, are a new dimension of quantitative precision oncology for PCa, and their independent prognostic value for BCR, overall survival, and treatment selection in theranostic programs needs to be prospectively validated in dedicated clinical trials, with standardized acquisition protocols across scanner types and PSMA radioligands (68Ga-PSMA-11 versus 18F-DCFPyL and 18F-PSMA-1007). The standardized PSMA-PET reporting based on the PROMISE system is like PI-RADS for MRI, providing the tools needed to integrate AI-derived metrics into the clinical context, making them clinically interpretable and reproducible. [25]

Digital Pathology

The validation of AI models in the PANDA challenge (blinded, strict external validation) over independent, cross-coastal cohorts ($\kappa = 0.86–0.87$), and the validation of AI models by Raciti et al. [33] in a clinical study, have been a substantial step forward in the clinical maturity of AI for PCa pathology in the last 1–2 years. This generalization is an essential requirement for regulatory clearance and clinical trial approval. Further evidence provided by Ji et al. [32] of the reliability of pathologist-level Gleason classification in a clinical laboratory establishes the translational value of AI Gleason grading as a standard-of-care tool to assist in routine reporting.

The new computational molecular pathology paradigm, which predicts genomic alterations from H&E WSI morphology,[36] could be a path to democratizing access to precision oncology for PCa patients in health systems without routine molecular testing capabilities. Loss of PTEN, mismatch repair deficiency, CDK12 mutations, and homologous recombination deficiency are examples of conditions that could be identified from WSI alone and could direct patients to PARP inhibitors, pembrolizumab, or platinum-based regimens, without the cost and turnaround time required for next-generation sequencing or dedicated immunohistochemistry. The next step in this domain for this application is prospective studies using these calculations as biomarkers in treatment decision algorithms.

Limitations and Future Directions

There is significant progress reported in this 2023–2026 review, but a number of key challenges to the clinical translation exist.

Firstly, most reported results are confined to the specific context of a single center and retrospective studies, and may be difficult to generalize. The limited number of AI systems reviewed has not been methodically evaluated for the transferability of trained models from high-volume academic medical centers to scanner hardware, imaging protocols, and diverse patient populations to support equitable and reliable clinical use.

Second, the absence of prospective, randomized clinical trials with patient-level outcomes such as cancer detection rate, unnecessary biopsy rate, time to diagnosis, treatment selection accuracy, and overall survival is the greatest impediment to clinical integration. The PI-CAI study provides an important

methodological model for such validation, but the same rigor should be used in all modalities.

Thirdly, there is no common method of evaluating AI systems. Differences in the performance metrics used across studies make comparison and pooling in meta-analysis difficult. If reporting standards are less rigorous than those of STARD-AI or CLAIM, the field can suffer from a growing optimism bias.

Fourth, none of the AI evaluation frameworks for PSMA-PET/CT or digital pathology are standardized, unlike those for MRI in PI-RADS v2.1. These are lacking, preventing direct comparison of AI systems and making pooled meta-analysis across studies with different endpoints and reference standards impossible.

Lastly, clinician acceptance, regulatory clearance, and medico-legal accountability are key concerns regarding model interpretability and explainability. While explainability is technically achievable, as shown by Hamm et al.,[10] XAI development incurs additional engineering costs for models and, in certain cases, may even reduce predictive accuracy relative to black-box models.

New paradigms, such as vision transformers (ViT), multimodal AI that combines imaging, pathologic, genomic, and clinical data streams, and large foundation models pre-trained on a wide variety of unlabelled medical imaging data, are set to usher in the next generation of PCa AI. A new yet rapidly growing paradigm is the use of foundation models trained via self-supervised pre-training on millions

Table 3.

Summary of key limitations, evidence gaps, recommended future directions, and expected clinical impact by modality

Domain	Current Limitation	Evidence Gap	Recommended Future Directions	Expected Clinical Impact
Multiparametric / Biparametric MRI	Inter-reader variability in PI-RADS 3 scoring persists; most AI models lack multi-centre external validation; annotation bottleneck limits training dataset scale.	No RCT demonstrates AI-assisted MRI biopsy decision-making improves patient outcomes (cancer detection rate, avoidable biopsy rate) vs. standard-of-care.	Prospective RCTs (e.g., PI-CAI framework) measuring cancer detection rate, unnecessary biopsy rate, and time-to-diagnosis as primary endpoints; standardized external validation protocols across scanner vendors.	Reduction of 20–30% unnecessary biopsies in PI-RADS 3 cohort; harmonized reporting across non-subspecialized centers; accelerated patient throughput.
Ultrasound / Micro-Ultrasound	Current micro-US AI studies are retrospective, single-center, and small (n<200); preprint studies not yet peer-reviewed; limited data on real-time intraoperative guidance accuracy.	Absence of head-to-head RCTs comparing AI-guided micro-US vs. MRI-targeted biopsy for csPCa yield; no health-economic analysis in resource-constrained settings.	Multicenter prospective trials comparing AI micro-US vs. MRI-TRUS fusion biopsy; real-time AI guidance validation; cost-effectiveness modelling in low-MRI-access health systems.	Democratized access to csPCa detection in low-resource settings; potential to replace MRI triage in appropriately selected populations.
PSMA-PET/CT	High inter-study variability in AI performance (sensitivity 62–97%); no standardized AI evaluation framework comparable to PI-RADS; limited generalizability across PSMA radioligands (68Ga vs. 18F agents).	Prospective validation of AI-derived prognostic biomarkers (total PSMA-avid tumor volume, lesion count, radiomic signatures) for BCR, overall survival, and treatment selection in theranostic programmes.	Prospective multicenter trials using PROMISE-aligned AI reporting; cross-radioligand validation studies; AI integration into theranostic dosimetry pipelines; RCT endpoints including OS and treatment selection accuracy.	Standardized AI-PSMA reporting reduces reporting time by >50%; AI-derived tumor burden metrics qualify as theranostic eligibility biomarkers.
Digital Pathology / WSI	Most validated AI systems perform binary PCa detection; Gleason sub-pattern and cribriform architecture AI grading remains nascent; regulatory clearance limited to few markets.	Prospective RCTs demonstrating AI Gleason grading reduces inter-pathologist variability and improves treatment allocation accuracy; AI molecular pathology predictions unvalidated as clinical biomarkers.	RCTs integrating AI Gleason grading in treatment decision pathways (active surveillance selection, RP vs. radiation threshold); multi-institutional validation of AI-predicted molecular alterations (PTEN, CDK12, MMR) as actionable biomarkers.	Standardized AI Gleason grading reduces inter-pathologist discordance by ≥30%; AI molecular pathology enables precision oncology without additional cost of NGS.
Cross-cutting / Methodological	Lack of prospective outcome data; heterogeneous reporting metrics; limited AI fairness andbias assessment across patient demographics; regulatory frameworks lagging behind innovation.	No established regulatory pathway for dynamic/adaptive AI models in prostate imaging; health equity data (AI performance across race, ethnicity, socioeconomic status) largely absent.	Adoption of CLAIM/STARD-AI reporting standards; prospective health equity evaluations; multimodal foundation models integrating imaging, pathology, genomics, and clinical data; LLM-based structured report generation for PI-RADS and PROMISE automated coding.	Universal reporting standards enable pooled meta-analysis; equitable AI deployment reduces diagnostic disparities; foundation models accelerate AI development for rare PCa subtypes.

of unlabelled images, which can be adapted to specific tasks, e.g., PCa lesion detection, using much less labeled data than traditional supervised learning.[39] Large language models (LLMs) in structured radiology and pathology reports for automated PI-RADS coding, PROMISE coding, clinical trial eligibility screening, and the development of treatment recommendation systems represent the emergency frontier of PCa AI. Table 3 summarizes the current limitations and future research needs by modality.

Conclusion

This literature review provides an overview of the latest evidence (2023–2026) on the use of AI across four medical imaging and pathology modalities for prostate cancer detection, characterization, and grading: multiparametric MRI, ultrasound/micro-ultrasound, PSMA-PET/CT, and digital pathology/whole-slide image analysis. The reviewed studies show that AI can achieve meaningful detection and characterization of PCa, with high accuracy, sensitivity, and specificity in all modalities. The PI-CAI study was conducted in a strictly validated pan-European setting and demonstrated that the ensemble AI systems outperformed the average radiologist reading level in detecting csPCa on bpMRI. The PANDA challenge demonstrated pathologist-level Gleason grading in external validation cohorts across continents. AI-enhanced micro-ultrasound systems have demonstrated significant diagnostic accuracy at biopsy for the diagnosis of csPCa. Segmentation and quantification of 68Ga-PSMA PET tumor volume using AI has been shown to be more reproducible and predictive than manual segmentation. In simulated and prospective clinical workflows, AI-augmented digital pathology has consistently achieved greater accuracy in PCa detection and concordance in Gleason grading.

Despite these developments, clinical integration will not be complete until there are multi-center, prospective, outcome-driven validation studies that are completed, AI evaluation and reporting frameworks are standardized, robust regulatory pathways are established that align with the needs of clinical transparency, and strategies to deploy AI are implemented that account for health system disparities in MRI access and specialist availability. This is an exciting new frontier of precision oncology for PCa, where imaging, pathology, and molecular information will all be integrated into a single diagnosis and prognosis. To realize this promise, long-term cooperation among imaging scientists, pathologists, urologists, oncologists, AI engineers, and regulators worldwide is necessary.

Author Contribution Statement

The author confirms sole responsibility for the conception, design, and writing of the manuscript.

Conflict of Interest

The author has declared no conflict of interest.

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