Advances in Science and Technology Research Journal

Advances in Science and Technology Research Journal, 2026, 20(6), 119–134
https://doi.org/10.12913/22998624/217042
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Received: 2025.11.29
Accepted: 2026.04.15
Published: 2026.05.01

Artificial intelligence in the diagnosis of endometrial pathologies: A review

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ABSTRACT

Artificial intelligence (AI) systems that aid in the diagnosis of many pathologies (including endometrial cancer) are gaining importance despite the limitations of traditional imaging and histopathological methods, as these are prone to subjectivity, inter-observer variability, and limited access to subspecialty expertise. This narrative review describes recent progress in the application of machine learning (ML) methods and deep learning (DL) approaches to hysteroscopic imaging, cytology, ultrasonography, magnetic resonance imaging, and multiomic data in selected endometrial conditions. Diagnosis based on AI techniques has shown good sensitivity and accuracy in the detection and classification of endometrial polyps, hyperplasia, and malignant lesions, with some models achieving performance comparable to that of experienced clinicians. Incorporating the expertise of diagnosticians through AI systems can enhance diagnostic workflows in terms of accuracy and efficiency. Innovations in optical biopsy during hysteroscopy, automated cytological analysis, and MRI-based lesion segmentation have been remarkable. While applications of AI are promising, the available evidence is limited by relatively small datasets, predominantly single-center study designs, a lack of external validation, and heterogeneity in imaging protocols, which together hinder generalizability to routine clinical practice. Other challenges include a lack of model interpretability, diminished robustness to subtle or atypical images, and barriers to integration of AI utilities into routine diagnostic practice. Future studies should concentrate on large-scale prospective validation, improving interpretability, and establishing multimodal diagnostic approaches that combine imaging data with clinical and molecular data, which will support clinical decision-making. These advances may lead to earlier detection, more consistent diagnostic assessment, and personalized risk assessment in endometrial diseases.

Keywords: artificial intelligence, machine learning, deep learning, endometrial pathology, hysteroscopic imaging, computer-aided diagnosis, radiomics.

INTRODUCTION

The application of artificial intelligence in medicine has expanded rapidly, particularly in diagnostic domains, and its clinical relevance is anticipated to increase further. This narrative review examines the current state of AI (artificial intelligence) research in endometrial pathologies. Although AI-related investigations are most prevalent in cervical cancer, studies focusing on ovarian and endometrial diseases remain comparatively limited. Across the available literature, small sample sizes and the lack of external validation emerge as the most frequently cited methodological limitations, especially in research concerning endometrial cancer and uterine sarcoma.

Recent advancements in computer science have substantially accelerated the development of AI, as contemporary AI systems can autonomously learn complex patterns from data to construct increasingly sophisticated predictive models. Within the medical field, AI methodologies have been applied predominantly to image-recognition tasks [1–4]. AI has been investigated across multiple medical specialties, with particularly strong performance reported in radiology, dermatology, ophthalmology, and colonoscopy [5]. Ben Ali Kaddour et al. developed an AI model capable of diagnosing 12 medical disorders with an accuracy of 90.47% [6]. AI has also been widely used in histopathology; for example, Liu et al. (2023) highlighted AI's ability to extract critical information from complex medical images and to support pathologists in selected diagnostic tasks [7]. However, the magnitude of clinical benefit varies by task and setting, and robust prospective evidence remains limited for many applications. There are several uses of different AI techniques for segmenting, classifying, and creating synthetic data from images, such as transfer learning, generative adversarial networks, and convolutional neural networks (CNNs) [8]. AI algorithms can identify subvisual structural characteristics that are difficult to quantify visually. In a pilot study on the diagnosis of breast cancer, the sensitivity for the detection of micrometastases rose from 83.3% (by a pathologist alone) to 91.2% (by a pathologist combined with a computer algorithm) [9,10]. The technology shows particular promise in cancer research, with Feng et al. (2024) noting AI's potential in early disease detection and precise treatment planning [11]. Moreover, DL (deep learning) models have been demonstrated to predict the status of selected molecular markers in lung, prostate, gastric, and colorectal cancer based on standard H&E (hematoxylin and eosin) slides [12].

However, progress in gynecologic oncology has lagged behind other disciplines, such as endoscopy, and existing AI tools do not yet meet the standards required for widespread clinical adoption [13]. Key barriers include limited external validation, dataset shift across devices and sites, and insufficient interpretability and workflow integration.

Diagnostic hysteroscopy is a minimally invasive procedure that provides direct visualization of the uterine cavity, enabling real-time assessment of both normal and pathological endometrium. This direct inspection supports more accurate preliminary diagnosis and guides subsequent clinical decision-making. A range of intrauterine abnormalities can be identified through hysteroscopic evaluation, including endometrial polyps, submucosal fibroids, intrauterine adhesions, endometrial hyperplasia, malignancies, intrauterine foreign bodies, retained products of conception, and endometritis [14]. Traditional hysteroscopy has its limitations, stemming from physicians' subjective judgment, which can lead to the inability to identify subtle lesions and the risk of misdiagnosis and missed findings. Furthermore, the technical aspects of the procedure can be problematic. Image quality can be compromised by factors such as lighting conditions and equipment variability. In addition, hysteroscopy is resource-intensive and requires operator expertise, and its use may be limited by patient tolerance and access to equipment. To address these challenges, the integration of DL-based decision support has been explored to improve lesion detection and classification during hysteroscopy. However, obtaining high-quality hysteroscopic image data remains a challenge, impacting model performance [15,16].

Endometrial cancer is a prevalent gynecologic malignancy with an increasing global incidence, largely attributable to rising obesity rates, lifestyle-related factors, and hormonal exposures. Despite advancements in therapeutic strategies, early symptoms are often nonspecific, frequently leading to delayed diagnosis. Prognosis is strongly stage-dependent: early-stage disease is associated with a 5-year survival rate approaching 90%, whereas advanced-stage disease yields survival rates below 20% [17]. This stark contrast underscores the critical need for more effective methods of early detection. Conventional diagnostic modalities such as ultrasonography, endometrial biopsy, and cross-sectional imaging are resource-intensive, demonstrate variable specificity, and remain prone to false positives in selected clinical scenarios.

AI, particularly DL-based approaches, has shown considerable promise in improving diagnostic accuracy. In the studies included in this review, DL models achieved a pooled sensitivity of 90% (95% CI, 84–94%) and a specificity of 94% (95% CI, 85–98%), suggesting high discriminatory performance under study conditions. These findings indicate that AI has the potential to enhance early detection and reduce the diagnostic burden associated with conventional screening strategies [18]. However, pooled estimates may be influenced by study heterogeneity, publication bias, and differences in reference standards and patient selection.

Several studies have incorporated clinical parameters to support diagnostic prediction. For example, Pergialiotis et al. utilized demographic and clinical data from 178 postmenopausal women presenting with vaginal bleeding or an endometrial thickness greater than 5 mm to predict histopathological outcomes [19].

Future research should prioritize large-scale, methodologically rigorous randomized trials and prospective cohort studies to validate the diagnostic accuracy of AI-based screening tools. Additionally, efforts should focus on the development and evaluation of integrated diagnostic models that combine AI-driven analytics with expert clinical judgment to optimize diagnostic performance and clinical applicability [18, 19].

The aim of this review is to provide a comprehensive overview of current advances in the use of AI in the diagnosis of endometrial pathologies, with particular focus on the effectiveness, limitations, and clinical applicability of ML (machine learning) and DL methods.

FOUNDATIONS OF AI IN CANCER DIAGNOSIS

Artificial intelligence has become one of the central driving forces of contemporary oncologic diagnostics, enabling the analysis of imaging, histopathological, and molecular data at a scale and level of reproducibility that can be difficult to achieve with conventional workflows alone. The rapid evolution of DL and ML has transformed how malignant lesions are detected and classified, supporting clinicians, reducing interobserver variability, and improving the overall quality and efficiency of diagnostic workflows. As early as 2019, Esteva et al. emphasized that AI-enabled medical computer vision systems can achieve diagnostic performance comparable to domain experts across several modalities [20]. Similarly, Topol noted that the integration of AI into clinical practice marks a shift toward "high-performance medicine," characterized by standardization, automation, and accelerated diagnostic decision-making [21].

One of the most advanced and clinically validated areas of application is radiology, where DL models have demonstrated high accuracy in early cancer detection in selected settings. In a landmark study, Ardila et al. showed that an end-to-end AI system analyzing low-dose computed tomography achieved performance comparable to experienced radiologists in identifying early-stage lung cancer, while simultaneously reducing false-positive findings in the evaluated workflow [22]. Likewise, McKinney et al. demonstrated that AI-based interpretation of mammography can reduce both false positives and false negatives more effectively than the classical double-reading workflow [23]. These systems operate with high throughput and deliver more consistent outputs than human readers, making them a valuable asset in imaging-intensive oncology settings.

Similarly transformative advances are observed in digital pathology. Whole-slide imaging (WSI) combined with CNNs enables the analysis of gigapixel histopathology slides in a largely automated manner. Coudray et al. provided evidence that AI can not only classify non-small cell lung cancer directly from hematoxylin-and-eosin (H&E) slides, but can also predict key oncogenic mutations such as EGFR or KRAS from morphology alone [24]. Comprehensive reviews, such as that by Litjens et al., confirm the broad potential of AI to grade tumors, detect subtle malignant foci, and improve interobserver agreement – a critical issue in traditional pathology workflows [25]. Importantly, these findings are echoed in broader clinical reviews such as that by Bi et al., who systematically outlined the translation of AI into cancer imaging and highlighted key challenges and opportunities in integrating AI systems into real-world oncologic diagnostics [26]. This reinforces the potential clinical relevance and feasibility of adopting AI-based tools in routine cancer workflow.

An example of a commercially deployed AI-based risk stratification tool outside gynecologic oncology is the ArteraAI Prostate Test [27]. This platform is a predictive and prognostic system based on DL analysis of digitized prostate biopsy whole-slide images, combined with clinical data. The model evaluates histopathological patterns at the pixel level to generate individualized risk scores for disease progression and treatment response, supporting personalized therapeutic decision-making in prostate cancer [28]. ArteraAI has demonstrated clinical validity/utility in specific decision contexts, including predicting the benefit of radiotherapy intensification and distinguishing patients who may safely undergo treatment de-escalation, representing a notable translation of AI-driven histopathology into clinical oncology practice [29,30].

Substantial progress has also been made in molecular diagnostics, a rapidly growing domain in the era of precision oncology. AI models can process complex datasets derived from genomic sequencing, including mutational signatures and gene-expression profiles, and utilize them to predict prognosis or responsiveness to targeted therapies. Kather et al. demonstrated that AI can infer microsatellite instability (MSI) – a pivotal biomarker for immunotherapy response –directly from histopathological images, potentially reducing reliance on specialized molecular assays in selected scenarios [31]. This capability may shorten diagnostic turnaround time and reduce the costs associated with advanced molecular testing.

AI applications extend to endoscopic and interventional oncology. Luo et al. introduced a real-time DL system capable of detecting colorectal polyps during colonoscopy, significantly increasing adenoma detection rates and thereby potentially reducing the risk of subsequent colorectal cancer development [32]. Comparable technologies are emerging in urology, otolaryngology, and gynecology, where AI supports classification of lesions in endoscopic, ultrasound, or other minimally invasive imaging modalities.

Furthermore, AI plays an increasingly important role in disease monitoring and treatment assessment. ML systems can analyze consecutive imaging studies, laboratory data, or clinical records to detect early signs of disease progression, evaluate treatment response, or predict therapy-related toxicity. As noted by Chen et al., AI-based decision-support models can analyze large patient populations to identify subtle clinical patterns and improve therapeutic stratification [33].

Despite these advances, several challenges must still be addressed, including the need for multicenter validation, reduction of dataset bias, improved model transparency, and effective integration into clinical infrastructures. Nonetheless, evidence suggests that AI is becoming an increasingly important component of modern oncologic diagnostics. Importantly, many of these technological developments are directly applicable to gynecologic oncology. AI-driven tools for ultrasound interpretation, automated histopathology, and real-time endoscopic assessment form the basis for emerging diagnostic approaches to endometrial pathology. Consequently, the following section examines the specific applications and current evidence related to AI in the evaluation of endometrial lesions.

AI APPLICATIONS IN THE DETECTION, CLASSIFICATION AND RISK STRATIFICATION OF ENDOMETRIAL LESIONS AND PATHOLOGIES

Endometrial polyps are defined as localized overgrowths of endometrial glands, stroma, and vasculature originating from the uterine lining. They may occur across a broad age range, with peak incidence observed between 40 and 49 years. Common clinical manifestations include abnormal uterine bleeding, pelvic discomfort, and infertility. Although the majority of polyps are benign, reported rates of malignant transformation vary from 0% to 13% [34–36]. Hysteroscopic polypectomy remains the standard therapeutic approach for symptomatic patients or those at elevated risk; however, the procedure is associated with potential complications, including intraoperative hemorrhage, uterine perforation, injury to adjacent pelvic structures, fluid overload, and the development of intrauterine adhesions [37].

Hysteroscopy has largely supplanted traditional cervical dilatation and curettage for the diagnostic evaluation of endometrial cavity disorders and is widely regarded as the gold standard for both diagnosis and management of intrauterine pathology. Within this framework, computer-assisted tissue characterization has emerged as a technique aimed at quantifying image-derived features to distinguish normal from abnormal tissue more objectively [38, 39]. Nevertheless, diagnostic accuracy remains dependent on the operator's expertise, introducing subjectivity and susceptibility to interobserver variability.

To mitigate these limitations, some investigators have developed CNN-based computer-aided diagnosis (CAD) systems capable of classifying five common endometrial lesions: endometrial hyperplasia without atypia, atypical hyperplasia, endometrial cancer, endometrial polyps, and submucous myomas. These models demonstrated diagnostic performance that was slightly superior to that of experienced gynecologists, highlighting the potential of AI to improve objectivity and accuracy in hysteroscopic evaluation [14]. However, most studies remain single-center and require external validation before clinical deployment.

Tanos et al. [38] reported their experience using CATIA (Computer-Aided Diagnosis by Tissue Image Analysis) as an optical biopsy tool in gynecologic oncology. The study aimed to identify quantifiable differences in image texture and related visual features between benign and malignant endometrial tissues, employing machine learning and artificial neural networks to improve diagnostic accuracy during minimally invasive gynecologic procedures. The initial investigation analyzed texture-based parameters from hysteroscopic images obtained from 40 patients, yielding 209 normal and 209 abnormal regions of interest (ROIs). A subsequent evaluation incorporated images from an additional 52 patients, comprising 258 normal and 258 abnormal ROIs, with all diagnoses confirmed through histopathological assessment.

The hysteroscopically identified ROIs were reported to align with histopathologic markers of malignancy, including architectural disruption, neoangiogenesis, edema, and cellular atypia. These findings highlight the capacity of CAD systems to approximate aspects of microscopic interpretation through computational analysis of endoscopic imagery.

The authors emphasize that CATIA requires further validation in large-scale, methodologically rigorous clinical studies. Evidence of improved diagnostic accuracy and enhanced sampling precision would support its incorporation into intraoperative decision-making and could mitigate complications associated with conventional diagnostic procedures, including hemorrhage, hematoma formation, malignant cell dissemination, infection, intrauterine scarring from repeated biopsies, and avoidable tissue injury. If confirmed in prospective randomized trials, CATIA-enabled optical biopsy has the potential to substantially advance clinical practice in minimally invasive gynecologic surgery [38].

Raimondo et al. [39] investigated the utility of DL approaches to support the diagnosis of endometrial pathologies using hysteroscopic imaging. Although hysteroscopy combined with endometrial biopsy remains the diagnostic gold standard, its accuracy is highly dependent on the clinician's expertise. To address this limitation, the authors conducted a monocentric retrospective cohort study (January–May 2021), reviewing clinical records, institutional databases, and hysteroscopic videos from women with histologically confirmed intrauterine lesions. A total of 1500 images from 266 patients were analyzed, encompassing benign focal lesions, benign diffuse lesions, and preneoplastic or neoplastic lesions.

The study developed DL models for the detection and classification of intracavitary uterine pathology, both with and without the inclusion of clinical variables such as age, menopausal status, abnormal uterine bleeding, hormonal therapy, and tamoxifen use. Convolutional neural networks were employed, with separate datasets used for model training and validation according to a predefined train/validation/test split.

Overall, the models exhibited moderate diagnostic performance in both lesion detection and classification into benign focal, benign diffuse, or preneoplastic/neoplastic categories. The integration of clinical parameters yielded only marginal improvement. These results highlight inherent limitations of hysteroscopic imaging, particularly for subtle premalignant conditions such as endometrial hyperplasia, which often present with nonspecific or minimally apparent visual features.

The authors conclude that while DL-based approaches hold promise as adjunctive tools in image-based gynecologic diagnostics, current model performance remains insufficiently validated for routine clinical implementation. The findings emphasize the need for larger, multicentric datasets and the development of more robust DL frameworks to achieve clinically meaningful diagnostic accuracy [39].

Given the prevalence of endometrial cancer and its frequent early-stage diagnosis, precise cytological assessment remains a critical component of patient management. ANNs, which are computational models inspired by biological neural processing, are particularly well suited for pattern recognition tasks involving complex morphometric data.

Makris et al. [40] evaluated the performance of a multi-layer perceptron ANN (artificial neural network) (ANN-MLP) for distinguishing benign from malignant endometrial nuclei in liquid-based cytology specimens. A total of 416 histologically confirmed samples representing a spectrum of endometrial conditions were analyzed. Ninety nuclei per case were assessed using a custom morphometric imaging system; half of the dataset was employed for model training and the remaining half for validation. At the nuclear level, the ANN-MLP (multi-layer perceptron artificial neural network) achieved an accuracy of 81.33%, with a specificity of 88.84% and a sensitivity of 69.38%. Performance improved at the case level, particularly when using a percentage-based classifier, which yielded an accuracy of 95.91%, specificity of 93.44%, and sensitivity of 99.42%. These results suggest that ANN-based systems may support cytological evaluation by promoting diagnostic consistency and potentially reducing observer variability [40]; however, the available evidence is limited by the lack of reported external validation and insufficient detail regarding patient-level, multicenter evaluation.

Similarly, Zhang et al. [14] developed a deep learning model utilizing hysteroscopic images from 454 patients with histologically confirmed intracavitary lesions. The system achieved an overall accuracy of 80.8% and correctly classified lesions as benign or premalignant/malignant with an accuracy of 90.8%. However, the study had notable limitations: it did not evaluate the model's ability to detect endometrial lesions in an end-to-end manner (i.e., lesion localization/identification before classification), nor did it assess whether the integration of clinical variables could further enhance diagnostic performance [14].

Zhao et al. developed a DL model designed for the real-time detection of endometrial polyps in hysteroscopic video recordings, achieving an accuracy of up to ~91% (internal test) and ~88% (external test). The system focused on polyp detection (CADe) rather than lesion type classification (CADx) [37].

To enhance real-time detection performance, the authors incorporated group normalization into the YOLOX architecture and implemented a video adjacent-frame association (VAFA) algorithm to improve detection stability. The model was trained and evaluated using 7313 polyp-containing frames and 4526 polyp-free frames extracted from 323 hysteroscopic videos, representing, to the authors' knowledge, the first application of DL for endometrial polyp detection in this context.

The study identified several limitations, including reduced accuracy when polyps were partially obscured or when floating endometrial tissue mimicked polypoid structures. These challenges could potentially be mitigated by expanding the training dataset to include additional occluded and background images. Although object-tracking algorithms such as Deep SORT may improve detection stability, further refinement of the VAFA algorithm is necessary, as it currently produces suboptimal smoothness in detection outputs. The authors highlight the need for more advanced algorithmic approaches and prospective clinical validation to establish the model's applicability in routine clinical practice [37].

Endometrial hyperplasia is a precursor to endometrial cancer, characterized by excessive glandular proliferation. Current classifications define two types of hyperplasia, each with a different risk of progression to endometrial cancer. These classifications rely on subjective visual assessment, which can lead to erroneous treatment decisions. In the present study, the authors developed an automated AI-based tool (ENDOAPP) for measuring morphological and cytological characteristics of endometrial tissue using Visiopharm software. ENDOAPP was used to extract features from images of tissue slides obtained from 388 patients diagnosed with endometrial hyperplasia between 1980 and 2007. The most prognostic features were identified using a logistic regression model and used to assign a low- or high-risk progression score. The tool demonstrated prognostic discrimination for progression risk, suggesting potential utility as decision support for risk stratification [41].

Early detection of endometrial cancer remains a critical priority, particularly in the absence of established population-based screening methods. Takahashi et al. [42] introduced an AI-based system for the automated identification of cancer-affected regions in hysteroscopic images. The study analyzed data from 177 patients, including 60 with normal endometrium, 21 with uterine myomas, 60 with polyps, 15 with atypical hyperplasia, and 21 with endometrial cancer. Three deep neural network (DNN) models were trained, and a continuity-analysis algorithm was developed to enhance diagnostic precision. The integration of these models was also evaluated [42].

Using standard classification procedures, the models achieved an accuracy of approximately 79-81%. The application of continuity analysis improved accuracy to ~84–89%, while ensembling all models yielded an overall accuracy of 90.29%, with a sensitivity of 91.66% and specificity of 89.36%. These findings underscore the potential of the proposed system to facilitate timely and accurate diagnosis of endometrial cancer under the study conditions.

Given the limited diagnostic role of hysteroscopy in routine screening and the constraints imposed by small training datasets, the study aimed to establish a high-performance diagnostic framework optimized for small-sample conditions. The results suggest that DNN-based analysis of hysteroscopic images can achieve promising accuracy and may provide a foundation for future large-scale, multi-institutional studies. Ultimately, such AI-driven systems have the potential to support clinical decision-making, including consideration of fertility-preserving management strategies, and may reduce reliance on invasive diagnostic procedures pending prospective validation [42].

With the increasing application of AI in medical image analysis, several studies have demonstrated the utility of object-detection and DL algorithms for identifying lesions in endoscopic images. In endometrial pathology, AI has been applied across multiple modalities, most prominently magnetic resonance imaging (MRI) and ultrasound, with a growing body of work in hysteroscopic imaging and digital pathology.

Studies have shown that preoperative MRI radiomics analysis in patients with EC (Endometrial cancer) may help assess tumor stage, deep myometrial invasion (MI), lymphovascular space invasion (LVSI), and lymph node metastasis [43].

Thanks to the image-recognition capabilities of CNNs, DL models have also been explored to improve the preoperative assessment of EC, particularly for quantifying the depth of MI. These algorithms can learn discriminative imaging patterns and may reduce reliance on manual feature engineering; however, many published pipelines still depend on manual or semi-automated segmentation, and fully automated end-to-end workflows remain less consistently validated across centers.

This may reduce the workload for radiologists and increase diagnostic efficiency. However, certain limitations should be noted, primarily due to the reliance on single-center and/or proprietary datasets, which necessitates validation on larger, multi-center cohorts. Furthermore, some studies rely on limited MRI sequences, without incorporating the full multiparametric MRI protocol (e.g., dynamic contrast-enhanced imaging where available). Therefore, to increase the versatility and accuracy of these models, future studies should integrate multi-sequence (multiparametric) MRI data and perform robust external validation [16].

Other authors also emphasize that applying neural networks (CNNs) to tumor images can be a useful tool not only for aiding image interpretation but also for risk stratification and treatment planning, although the maturity of evidence differs by task. Accurate lesion localization/segmentation is often a critical prerequisite for downstream prediction tasks [44].

Hodneland et al. [45] employed a three-dimensional convolutional neural network (3D CNN) to automate the segmentation of endometrial cancer on MRI, reporting that CNN-based segmentation and tumor volume estimation achieved performance approaching that of manual segmentation performed by experienced radiologists [45]. Similarly, Kurata et al. utilized a CNN (convolutional neural network) for multi-sequence MRI-based segmentation of uterine endometrial cancer [46].

Additional studies have focused on enhancing diagnostic precision and evaluating tumor invasion depth. Zhang et al. trained and validated a LeNet-5 neural network using MRI data from 158 patients with endometrial cancer, achieving an area under the curve (AUC) of 89.7% [47]. Dong et al. applied a U-Net neural network to MRI scans to assess the depth of endometrial cancer invasion, achieving a model accuracy of 79.2%, which did not significantly differ from the diagnostic performance of radiologists [48].

Integration of multimodal imaging has also been explored. Xia et al. [49] developed a DPA-UNet network to support endometrial cancer assessment using hysteroscopic imaging alongside ultrasonography [49], while Wang et al. [50] employed a 3D U-Net network for automatic endometrial segmentation and thickness measurement in 3D transvaginal ultrasound (3D TVUS) images [50]. Collectively, these studies underscore the potential of DL techniques to enhance the accuracy, reproducibility, and efficiency of imaging-based diagnosis in endometrial pathology, although broader clinical adoption will require external validation and prospective evaluation across diverse acquisition settings.

Ultrasound is a key tool for initial lesion detection, enabling imaging of endometrial thickness, homogeneity, and the presence of endometrial abnormalities. Deep learning has been widely investigated in ultrasound imaging in other domains (e.g., breast imaging), supporting the feasibility of similar approaches in gynecology. DL methods have been used to analyze ultrasound images for the assessment of EC, including evaluation of myometrial invasion (MI) severity and lesion characteristics [51–54].

There are limitations resulting from the need for high-quality ultrasound images, which hinders the widespread implementation of DL models in clinical settings. It is important to remember that the quality of ultrasound images is influenced by the operator's skill level, the quality of the equipment, and the patient's body composition. These factors can introduce data variability and complicate model training. Future research should focus on standardized acquisition protocols and the development of multicenter, curated datasets [16].

One study was conducted using data from 302 patients treated at the Mayo Clinic for postmenopausal bleeding between 2016 and 2021. The study utilized a set of retrospectively collected ultrasound images. Patients who underwent transvaginal ultrasound examination and subsequent endometrial sampling within 3 months of the examination were included. Exclusion criteria included missing data regarding endometrial sampling or a procedure performed elsewhere, as well as a diagnosis of hyperplasia without atypia or non-epithelial histology on histopathological examination.

Patients were divided into two groups: group A (atypical hyperplasia/cancer) and group B (benign), based on the pathologic report of endometrial sampling. The transvaginal ultrasound examinations were analyzed by two highly experienced radiologists (level III training in gynecological ultrasonography) and two gynecologists with level I training in gynecological ultrasonography. In the first phase, a fully automated image segmentation model was developed to identify/segment the endometrial layer using images with corresponding manual segmentations. In the second phase, an AI-based classifier model was developed: radiomic features were calculated from manually segmented regions of interest and used to train multiple ML-based classifiers. The performance of the classifier model was assessed using a threefold evaluation/cross-validation strategy. The reference standard was the pathological outcome of endometrial sampling, enabling classification into benign and premalignant/malignant cohorts.

The authors developed an AI-based algorithm to distinguish atypical endometrial hyperplasia/cancer from benign conditions on transvaginal ultrasound images in patients with postmenopausal bleeding [55], reporting strong discriminatory performance in internal validation and a hold-out test set.

A recent study by Erdemoglu et al. [56] evaluated the use of AI for predicting endometrial intraepithelial neoplasia and endometrial cancer in pre- and postmenopausal women. The study analyzed data from 564 patients and applied multiple ML algorithms, including random forest, logistic regression, multilayer perceptron, CatBoost, XGBoost, and Naive Bayes. Clinical and demographic variables – such as age, menopausal status, abnormal uterine bleeding, body mass index (BMI), comorbidities, smoking history, and endometrial thickness – were incorporated into the models. The best-performing model achieved an accuracy of 94% and an AUC (area under the curve) of 93.8%, with age, BMI, and endometrial thickness emerging as the strongest predictors of precancerous and cancerous endometrial pathology [56]. These findings highlight the potential of AI to facilitate personalized risk assessment and early identification of endometrial disease; however, broader clinical implementation will require larger, more diverse datasets and rigorous external validation to ensure model robustness and generalizability.

The researchers showed that an ML algorithm (XGBoost) may help predict endometrial cancer recurrence. The model incorporated demographic, clinical, laboratory, imaging, surgical, and pathological variables, including age, chronic metabolic diseases, family and personal cancer history, hormone replacement therapy use, endometrial thickness, uterine polyp presence, complete blood count results, albumin, CA-125 level, surgical staging, histology, depth of myometrial invasion, LVSI, grade, pelvic washing cytology, and adjuvant treatment. By integrating these inputs, the model aimed to stratify recurrence risk and could potentially help identify patients who might benefit from closer surveillance or tailored adjuvant management, pending external validation and prospective evaluation [57].

AI represents an increasingly valuable tool in the management of endometrial cancer (EC). ML models can integrate extensive clinical, pathological, and imaging datasets to support early diagnosis, risk stratification, prognostic prediction, and individualized treatment planning. Such approaches may enable the identification of high-risk patients, guide therapeutic decision-making, and facilitate monitoring of treatment response. Furthermore, AI can support preoperative planning, provide decision support intraoperatively, assist surgical training, and potentially reduce diagnostic errors and clinician workload. By improving staging accuracy through integrated analysis of clinical and imaging data, AI can inform optimal management strategies. Despite these advantages, challenges remain, including ethical considerations, potential data biases, and the need for comprehensive validation studies. Overall, AI holds considerable promise for advancing EC diagnosis and management, although further research is necessary to establish its clinical utility and delineate its limitations [58].

Zhao et al. [59] developed a predictive diagnostic model for endometrial carcinoma (EC) aimed at improving molecular discrimination and early detection. The global incidence and mortality of EC have been increasing, and although early-stage disease is highly curable, many cases are diagnosed at advanced stages, where treatment options are limited. Current diagnostic approaches, including clinical assessment, laboratory testing, imaging, and hysteroscopic biopsy, provide useful diagnostic performance but are constrained by limited specificity, invasiveness, patient discomfort, and cost, highlighting the need for more efficient and accurate diagnostic tools [59].

Machine learning, particularly DL, offers powerful analytical capabilities for large-scale genomic and transcriptomic data. Zhao et al. [59] leveraged RNA sequencing datasets from GEO (Gene Expression Omnibus) and TCGA (The Cancer Genome Atlas) to perform transcriptomic analyses, applying random forest and ANN algorithms to identify 14 EC-associated signature genes. Using these genes, they constructed a diagnostic model that demonstrated good performance across three independent EC cohorts, effectively distinguishing EC patients from non-cancer controls within the included datasets. The study also identified a significant inverse relationship between activated and resting mast cells within the tumor immune microenvironment, providing additional insight into EC pathogenesis. These findings offer a promising foundation for the development of molecular diagnostic tools and warrant validation in larger prospective studies [59].

Endometrial biopsy with histopathological evaluation remains the gold standard for EC diagnosis. However, the growing global shortage of pathologists poses a barrier to timely and accurate assessment. To address this challenge, the study introduced HIENet, a convolutional neural network incorporating attention mechanisms designed for the evaluation of hematoxylin-and-eosin (H&E)–stained endometrial tissue. HIENet enables automated image classification while improving interpretability through visualization of key histopathological features, including glands, stroma, and thick-walled vessels [60].

HIENet demonstrated promising performance in both binary and multiclass classification tasks using a dataset of 3500 H&E image patches, outperforming three associate chief physicians in tenfold cross-validation and external testing. Attention maps provided pixel-level correlations with diagnostic morphology, enhancing transparency and supporting clinical interpretability. These results suggest that HIENet could facilitate a human–machine collaborative workflow, improving diagnostic efficiency and promoting more consistent grading of endometrial pathology [60], although prospective validation at the patient/slide level and evaluation across multiple laboratories and scanners remain important next steps.

Currently, the traditional histological subtype-driven classification of endometrial cancer has shifted to a molecular-based classification that stratifies EC into DNA (deoxyribonucleic acid) polymerase epsilon mutated (POLEmut), mismatch repair deficient (MMRd), and p53 abnormal (p53abn), and classifies the remaining EC as no specific molecular profile (NSMP). The molecular EC classification has been incorporated into the World Health Organization 2020 classification and the 2021 European treatment guidelines [61].

This shift requires the use of additional molecular tests in routine diagnostics. Consequently, it can be challenging to assign clinically relevant weights to histological and molecular features in individual patients. Deep learning has been explored as an approach to enable integrated analysis of digitized histopathology, multimodal imaging, and molecular data in relation to clinical outcomes. If robustly validated, DL models capable of predicting the four molecular classes from routine data could potentially reduce reliance on molecular assays in selected workflows (e.g., as a triage or decision-support step), while confirmatory testing would likely remain necessary for equivocal or high-stakes cases. External generalizability is essential; in principle, such models could support molecular classification from digitized H&E slides, but this requires rigorous multicenter validation and careful assessment of failure modes. Potential benefits include lower incremental testing costs, reduced turnaround time, and streamlined workflows; however, these downstream impacts should be demonstrated in prospective clinical-effectiveness studies.

The goal of DL technology, combined with gynecological pathology expertise, is to highlight the clinical significance of morphological features associated with the four molecular subclasses of EC, while deepening the morphological and biological understanding of genomic changes in EC. Integrating molecular, clinical, and DL-derived information may improve EC classification and support prognosis and treatment prediction in patients with EC [62].

Magnetic resonance imaging (MRI) remains central to EC assessment and staging; however, diagnostic performance varies considerably, particularly for key prognostic indicators such as deep myometrial invasion and nodal metastasis. Limitations include reported moderate sensitivity (43%) and specificity (73%) for nodal involvement, operator-dependent variability, and the predominantly qualitative nature of conventional radiologic interpretation, which may inadequately reflect tumor biology. Despite attempts to standardize imaging protocols, guideline adoption remains inconsistent.

Radiomics and AI offer promising approaches to overcome these limitations. Radiomics extracts quantitative, high-dimensional features from imaging data that capture tumor heterogeneity and phenotypic characteristics, while AI algorithms can integrate these features to improve risk stratification, treatment planning, and prognostic prediction. Although preliminary studies are encouraging, current research is hindered by heterogeneous datasets, methodological inconsistencies, and a lack of robust external validation. Consequently, while radiomics and AI have substantial potential to enhance MRI-based EC assessment, further development is required to achieve reproducibility and clinical implementation [63].

Despite the transformative impact of AI across multiple medical specialties, its application in gynecologic oncology – particularly in EC – remains comparatively underexplored. Deep learning has demonstrated notable utility in radiology and other diagnotic domains by reducing clinician workload, minimizing human error, and improving the speed and accuracy of decision-making. Nonetheless, the integration of AI into EC diagnosis and risk prediction is still in its early stages, highlighting a significant area for future research and clinical translation. Table 1 presents the most important information regarding the studies included in this review.

To visually summarize study-level performance across heterogeneous datasets and tasks, we present comparative plots of segmentation accuracy (Dice/DSC) by modality (Figure 1) and the sensitivity–specificity trade-off for selected diagnostic models (Figure 2).

LIMITATIONS AND PERSPECTIVES

Methodologically, current AI studies in endometrial pathology are limited by small-scale, often single-center datasets and a lack of external validation, which undermine the strength of their findings. Inconsistencies across study designs and data sources further complicate comparisons between investigations. Notably, diagnostic performance can vary by imaging modality and by the level of evaluation (patient-, image-, or ROI-level). For instance, AI algorithms for hysteroscopic images can struggle with subtle or obscured lesions. Similarly, cytology-based models have shown reduced sensitivity at the cellular level, and systems developed for MRI often remain confined to a restricted set of sequences or single-vendor acquisition settings, limiting their broader applicability. These methodological weaknesses

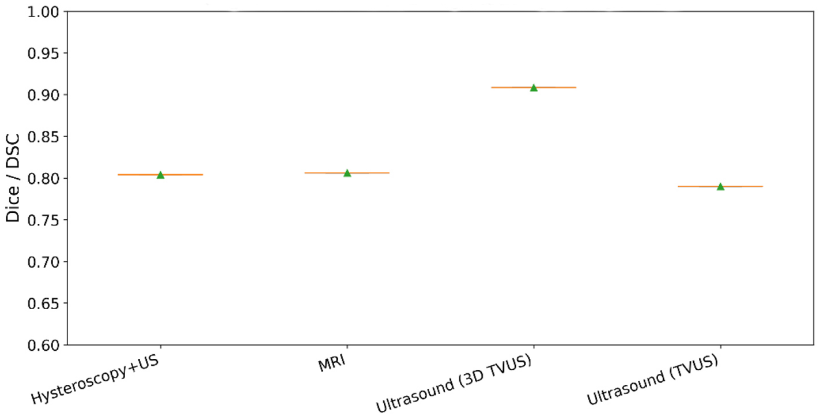

Figure 1. Segmentation Dice/DSC by modality (study-level). Boxplots summarize study-level Dice similarity coefficients (DSC) reported for automated segmentation tasks across imaging modalities (MRI, transvaginal ultrasound, and hysteroscopy combined with ultrasound). Each data point corresponds to a single study-level result; the mean value is indicated on the boxplot. Because the number of included studies per modality is limited and evaluation protocols differ between studies, these values should be interpreted as a descriptive comparison rather than a formal meta-analytic estimate.

Table 1. Summary of AI applications in endometrial pathology

Study	Modality / Data type	AI Approach	Sample / Cohort	Results	Limitations
Tanos et al. [38]	Hysteroscopic images	SVM using YCrCb color texture	40 patients (209+209 ROI) + additional 52 images (258+258 ROI)	Acc 81%, 78% Sens, Spec 81%	Requires larger datasets and further clinical validation; limited sample size
Raimondo et al. [39]	Hysteroscopic videos	Deep Learning, fine-tuned ResNet50 with pipeline to Detectron2-style RCNN-FPN with ResNet50 backbone	1500 images from 266 patients	Classification overall Acc 86.74%, Prec/Rec/Spec/F1 80.11/80.11/90.06/80.11; Identification Detection 85.82%, Prec/Rec/F1 93.12/91.63/92.37	Sensitivity limited by subtle visual features; insufficient for clinical use
Makris et al. [40]	Liquid-based cytology	Supervised MLP-ANN	416 smears: 168 healthy, 152 malignancy, 52 hyperplasia w/o atypia, 20 hyperplasia w/ atypia, 24 polyps	Nucleus-level: Acc 81.33%, Spec 88.84%, Sens 69.38%; Case-level numeric classifier: Acc 90.87%, Spec 93.03%, Sens 87.79%; Case-level percentage classifier: Acc 95.91%, Spec 93.44%, Sens 99.42%	No external validation/multicenter evaluation reported; single train-test split; potential within-patient dependency (90 nuclei/case) and class imbalance
Zhang et al. [14]	Hysteroscopic images	CNN image classifier: tuned VGGNet-16	454 patients; 1851 images (augmentation)	5-class Acc 80.8%; binary Acc 90.8%, Sens 83.0%, Spec 96.0%	No external validation; limited test set size (250 images); unclear handling of class imbalance
Zhao et al. [37]	Real-time hysteroscopic video converted to frames	DL, YOLOX + VAFA	323 videos; 7313 polyp frames and 4,526 polyp-free frames	internal (MCH) Acc 90.91%, Sens 100%, Spec 88.52%; external (TJH) Acc 88.0%, Sens 92.0%, Spec 76.0%	Reduced accuracy for occluded polyps; VAFA requires refinement; no lesion classification
Takahashi et al. [42]	Hysteroscopic images	DNN with continuity analysis	177 patients	Acc 90.3%, Sens 91.7%, Spec 89.4%	Small dataset; potential class imbalance; limited generalizability
Hodneland et al. [45]	MRI	3D U-Net CNN (UNet3D)	139 endometrial cancer patients based on preoperative pelvic imaging	Tumor volumes: no difference in median volume between raters and ML (Friedman p=0.28); log-volume agreement ICC: inter-rater 86% vs ML-to-raters 76%	MRI-focused; small training cohort; retrospective design
Kurata et al. [46]	Multi-sequence MRI	U-net CNN	200 EC patients (pretreatment MRI 2004-2017)	Test DSC 80.6%, Sens 81.6%, PPV 83.4%	Single-center retrospective design; needs external validation
Zhang et al. [47]	MRI	LeNet-5 CNN	158 patients	AUC (radiomics): 89.7% training, 88.9% test; AUC (comprehensive): 91.3% training, 89.7% test	Single-center cohort with all subjects from one hospital; single MRI instrument; limited sample size
Dong et al. [48]	MRI	U-Net CNN with fine-tuned pretrained encoders (VGG11/VGG16/ResNet34)	72 patients - 4896 MRI images (3456 slices of contrast-enhanced T1w, and 1440 slices of T2w)	Stage IA/IB ACC: AI 79.2% (CE-T1w) and 70.8% (T2w) vs radiologists 77.8%	Single-center, retrospective study with a small training cohort; limited MRI inputs
Xia et al. [49]	Hysteroscopic images with ultrasound images	DPA-UNet, compared with U-Net and Dense-Net	80 EC patients	DSC 80.4±18%, Prec 80.1±15%, Rec 87.6±11%	Small sample size; external validation needed
Wang et al. [50]	3D ultrasound volumes	3D U-Net	85 cases of 3D TVUS images	Test: DSC 90.83%, Jaccard 83.35%, Sens 90.85%	Limited clinical testing; small, imbalanced cohort

Table 1. Cont.

Erdemoglu et al. [56]	Clinical / demographic	MLP, RF, Logistic regression, CatBoost, XGBoost, Naive Bayes	564 patients	AUC 93.8%-94%, Acc 94%, test: Prec 71%, Rec 50%, F1-score 51%	Low event rate; class imbalance; no external validation; recall relatively low
Zhao et al. [59]	GEO microarray + TCGA RNA-seq	Random forest, ANN	822 total samples across 3 cohorts	Acc 88.2%/86.4%/ 83.9% (train/test/ validation); AUC 92.8%/92.1%/78.2% (train/test/validation)	Public transcriptomic datasets only; further clinical validation needed
Jiang et al. [16]	Ultrasound, MRI, Hysteroscopy, histopathology images	CNN with attention (U-Net/3D U-Net, ResNet/VGG/ EfficientNet)	Narrative literature review (no original patient cohort reported); synthesizes previously published endometrial cancer AI studies across ultrasound, MRI, hysteroscopy and histopathology datasets	DL can autonomously extract complex features and achieve high accuracy for EC discrimination and prognosis stratification across modalities	Models rely on limited/proprietary datasets, need multicenter/ multisource validation for real-world generalizability; image quality variability
Capasso et al. [55]	Ultrasound images	Automated TVUS endometrium segmentation plus radiomics-feature selection (mRMR) and an SVC classifier	302 patients	Segmentation: AI vs reader Dice 79% (inter-reader Dice 83%); Classification: AUC-ROC 90% (val) / 88% (test); F1-score 76%, Sens 87%, Spec 86%	Selection bias; limited diversity; classifier built on manual ROIs
Rewcastle et al. [41]	whole-slide images of PAN-CK+ immunostained FFPE endometrial hyperplasia tissue sections	Automated feature extraction tool ENDOAPP built in Visiopharm; logistic regression selects prognostic features	388 patients	AUC 76.5%; prognostic accuracy 88-91% (D-score 91%, higher than WHO94/ WHO20/EIN 83-87%); reproducibility ICC 83% (operators) and 79% (scanners)	Retrospective historical cohort with limited external validation; moderate discriminative power AUC ~76.5%
Violante Di Donato et al. [43]	MRI with radiomics/ texture features	MRI-radiomics + ML risk-prediction models	15 studies, 3608 patients	Meta-analysis pooled sens/spec - Grade 3 79/81%, deep myometrial invasion 74/82%, LVSI 66/75%, nodal metastasis 83/74%	Retrospective analysis; methodological heterogeneity; lack of standardization; limited external validation

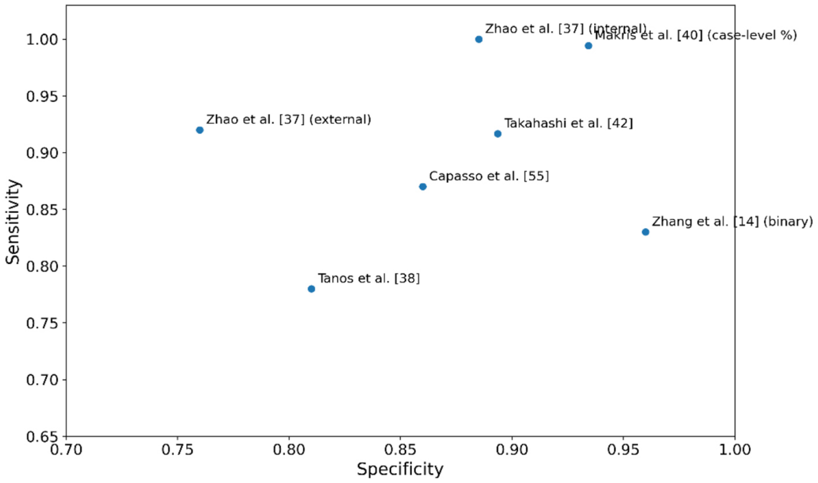

Figure 3. Sensitivity versus specificity of AI models (study-level). Scatter plot of sensitivity and specificity values reported for AI-based diagnostic models across included studies. Each point represents a study-level estimate for the specified endpoint (e.g., binary classification or detection); labels indicate the corresponding study. As performance metrics were derived from heterogeneous datasets and evaluation designs (e.g., patient-level vs image-level assessments, internal vs external testing), direct comparisons should be interpreted cautiously.

underscore the need for larger, more standardized studies to fully validate AI-driven diagnostics in diverse clinical settings.

Beyond study design issues, limitations inherent to the AI models themselves must be acknowledged. One major concern is the opaque "black-box" nature of many DL algorithms, which lack interpretability and hinder clinician trust. Model performance may also degrade in atypical or complex cases not well represented in the training data. For example, an AI system for polyp detection showed markedly reduced accuracy when lesions were partially obscured or when benign tissue mimicked polypoid structures. Such failures in unusual scenarios highlight model fragility outside the training scope. In addition, the use of small training sets without external validation fosters overfitting: algorithms can appear accurate on internal data but generalize poorly to new patient populations. Addressing model interpretability and robustness is therefore critical before clinical deployment.

Even with high-performing models, practical and system-level barriers have slowed the translation of AI into routine clinical practice. A chief hurdle is the dependence on high-quality, expert-labeled data: many models to date have been trained on limited or homogeneous datasets, underscoring the need for more diverse, multi-institutional data to ensure broad applicability. Integration with existing clinical workflows is another challenge, as current AI tools often lack interoperability with hospital information systems and imaging platforms, complicating real-world implementation. Furthermore, clear regulatory standards and guidelines for AI-driven diagnostics are still evolving, leading to variability in evaluation protocols and validation practices across studies. Concerns about data bias and ethics also persist, since algorithms can inadvertently reflect biases in their training data and typically do not explain their reasoning. Overcoming these barriers will require not only technical innovation but also consensus among clinicians, researchers, and regulators to establish trust, standardization, and governance for AI in endometrial pathology.

Future research should address these shortcomings with more robust and integrative strategies. High priority should be given to conducting large-scale, prospective multicenter studies that validate AI algorithms across diverse patient populations, while simultaneously establishing standardized evaluation metrics to consistently benchmark performance and facilitate comparability across studies and regulatory approval. In parallel, the development of explainable AI (XAI) techniques is crucial to make model decision-making transparent and trustworthy for end-users. Integrating multiple data modalities – for example, combining hysteroscopic imaging with MRI, ultrasound, and molecular data – may further improve diagnostic accuracy, as early multimodal studies have demonstrated potential performance gains by leveraging complementary information. Equally important is the exploration of clinician – AI collaboration frameworks: by integrating AI-driven analytics with expert clinical judgment, such "human-in-the-loop" models can maximize diagnostic efficacy while preserving accountability.

CONCLUSIONS

Artificial intelligence, encompassing ML and DL techniques, demonstrates substantial potential to enhance the diagnosis, risk stratification, and management of endometrial pathology. Across the studies reviewed, AI has been applied to diverse modalities, including hysteroscopic imaging, cytology, ultrasound, magnetic resonance imaging, histopathology, and transcriptomic datasets, highlighting its versatility and capacity to support precision medicine.

In hysteroscopy, CNN-based and computer-aided diagnostic systems, such as CATIA, have shown promise in automating the detection and classification of intrauterine lesions, improving diagnostic consistency, and reducing interobserver variability. In selected studies, model performance approached that of experienced clinicians; however, limitations remain, including small datasets, lesion occlusion, and variability in visual presentation, underscoring the need for larger, multi-institutional validation studies.

In cytological assessment, ANN-based systems demonstrated improved accuracy and reproducibility in distinguishing benign from malignant endometrial nuclei, supporting AI as an adjunct to traditional cytological evaluation. Similarly, DL models applied to MRI and ultrasound data have enabled automated tumor segmentation, assessment of invasion depth, and in some cases multimodal imaging integration, achieving performance comparable to radiologists in specific tasks while offering the potential for quantitative, reproducible measurements.

Predictive modeling using clinical, demographic, and transcriptomic data has further expanded AI's role in personalized risk assessment. ML algorithms incorporating patient characteristics and gene-expression signatures demonstrated promising discriminatory performance for detecting precancerous and cancerous endometrial conditions within the evaluated cohorts, highlighting AI's potential to support early diagnosis, guide surveillance strategies, and inform individualized management.

Despite these promising results, several challenges must be addressed before widespread clinical implementation. Common limitations include small and heterogeneous datasets, lack of external validation, variability in operator-dependent modalities, and limited interpretability of certain DL models. Moreover, ethical considerations, potential biases in data, and the need for standardized evaluation protocols remain critical concerns.

Overall, AI represents a transformative tool with the capacity to improve the accuracy, efficiency, and objectivity of endometrial cancer diagnosis and management. Integration of AI into clinical workflows has the potential to streamline diagnostic pathways and support decision-making, but claims of reduced invasiveness, improved outcomes, or fertility-preserving management require prospective clinical-effectiveness studies.

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