Transforming Gynecologic Cancer Care Through Artificial Intelligence

A Clinician's Guide to the Evolving Landscape

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Abstract: Artificial intelligence (AI) is rapidly reshaping gynecologic oncology across the continuum of care. This clinician-focused review synthesizes current evidence for AI-enabled prevention and screening (HPV-informed risk models, AI-assisted colposcopy), early detection and diagnosis (radiomics, liquid biopsy, and digital pathology), prognosis and risk prediction (multimodal models integrating clinical, imaging, histology, and genomics), and treatment guidance (surgical planning and response-predictive therapeutics). Across domains, deep learning and emerging multimodal models consistently match or surpass conventional approaches, offering gains in accuracy, speed, and reproducibility while enabling biologically informed decision support. We outline practical pathways for clinical integration, human-in-the-loop workflows, explainable outputs, and ethical and regulatory guardrails. Priority future directions include rigorous prospective trials, real-world performance tracking, and equity-centered deployment to ensure benefits generalize across diverse populations. Taken together, AI has the potential to enhance precision, consistency, and access in gynecologic cancer care, not by replacing clinicians, but by augmenting expertise at scale.

Key Words: artificial intelligence, gynecologic oncology, machine learning, deep learning, multimodal integration

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Gynecologic cancers account for a substantial and growing share of the global cancer burden.[1] Incidence of endometrial cancer continues to rise in many high-income countries, ovarian cancer remains the deadliest gynecologic malignancy due to late presentation, and cervical cancer, though preventable with HPV vaccination, still causes unacceptably high morbidity and mortality, particularly in low-resource settings.[1] Across this spectrum, outcomes depend on timely detection, accurate diagnosis, risk-aligned treatment, and sustained attention to survivorship and quality of life. At each step, current workflows face real constraints: subjective interpretation (eg, colposcopy, histologic grading), fragmented data (clinical, imaging, molecular), variability in access to subspecialty expertise, and limited capacity for continuous monitoring. These gaps create an opportunity to evaluate tools that can help clinicians deliver more consistent, equitable, and personalized care.

Artificial intelligence (AI) has become relevant now not because it is new, but because several enabling factors have converged. First, routine digitization of clinical data (via the electronic health record [EHR]), radiologic and histologic data has created large, labeled datasets. Second, multiomics testing (genomics, transcriptomics, methylation, and proteomics) is increasingly incorporated into gynecologic oncology practice, generating rich signals that can be learned from. Third, modern computing, including specialized hardware and cloud environments allow training and deployment of complex models at clinical timescales. Finally, the EHR has matured enough to support integration of models that synthesize longitudinal clinical data, patient-reported outcomes, and treatment exposures. Together, these advances shift AI from isolated proofs of concept to systems that can realistically sit alongside clinicians and augment decision-making.

For clinicians, a few terms anchor the discussion. Machine learning (ML) refers to algorithms that learn patterns from data to make predictions; traditional examples include logistic regression, random forests, and gradient boosting. Deep learning (DL) is a subset of ML that uses multilayer neural networks, particularly effective for images (eg, histology, MRI/CT/ultrasound), waveforms, and other high-dimensional data. Natural language processing (NLP) encompasses methods that extract and structure information from text such as pathology reports, operative notes, or trial eligibility criteria. Foundation models are large models pretrained on vast datasets (images, text, or both) that can be adapted to new tasks with relatively small amounts of labeled data; in pathology and radiology, such models often provide stronger generalization across scanners, stains, and institutions. Finally, federated learning enables training models across multiple sites without moving patient data off-premises, an approach that can improve representativeness while preserving data sovereignty and privacy.

Crucially, AI in gynecologic oncology should be framed as assistive technology. The aim is not to replace expert judgment, but to reduce unwarranted variation, surface relevant signals quickly, and support decisions that are biologically and contextually informed. That means models must be externally validated, explainable enough to support clinical trust, and embedded into workflows that respect existing guidelines and regulatory expectations.

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Equity is central: datasets and evaluations must reflect the diversity of the populations we serve, and deployment should narrow disparities in access and outcomes.

This review is organized around the patient care continuum, Figure 1, reflecting how clinicians and patients actually experience care. We first examine *prevention, screening and risk stratification*, including AI-enabled approaches to cervical screening, colposcopic assessment, and population-level risk models for endometrial and ovarian cancer. We then address *early detection and diagnosis*, spanning ultrasound, cross-sectional imaging, digital pathology, and multimodal integration that links morphology with molecular biology. Next, we detail *prognosis and risk prediction*, highlighting models that estimate recurrence and survival using clinical, imaging, histologic, and genomic features. We follow with *treatment guidance*, covering surgical planning and intraoperative assistance, radiation planning and adaptation, and data-driven selection of systemic therapies. We then discuss *toxicities and quality of life*, where AI supports proactive toxicity prediction, monitoring, and survivorship care. Finally, we outline *implementation challenges and ethical considerations* and close with *future directions* focused on multimodal foundation models, clinical integration, and rigorous prospective evaluation.

Our goal is pragmatic: to equip clinicians with a clear, clinically grounded understanding of what AI can and cannot do today in gynecologic oncology, what evidence is still needed, and how these tools can be responsibly integrated to advance precision, consistency, and equity in care.

PREVENTION, SCREENING, AND RISK STRATIFICATION

Identifying strategies for prevention, screening, and accurate risk stratification is critical for improving outcomes and optimizing resource allocation for gynecologic malignancies. Traditional screening methods, while effective, are limited by subjectivity, accessibility, and sensitivity, particularly for early-stage disease. AI-enabled systems can integrate multiple data sources, including patient characteristics, genetics, imaging, and cytology to improve prevention, screening, and risk prediction.

Substantial research in cervical cancer has applied AI to enhance screening, risk stratification, and prevention. Models that integrate behavioral, social, and biological variables generate comprehensive risk profiles to support counseling, optimize screening intervals, and guide HPV vaccination outreach.[2] AI has also been increasingly applied to colposcopic image analysis, one of the most subjective and operator-dependent steps in cervical cancer evaluation. Across multiple studies, DL models have demonstrated strong performance for automated lesion detection, classification, and biopsy guidance, often matching or exceeding the diagnostic accuracy of experienced colposcopists.[3] These systems can identify transformation zones, highlight suspicious regions, and support consistent interpretation, thereby reducing interobserver variability. Multimodal frameworks that combine colposcopic imaging with cytology and HPV testing have achieved near-perfect performance and exemplify the potential of AI to unify complementary data streams for real-time decision support.[4] Collectively, these advances highlight AI-assisted colposcopy as a scalable approach to standardize evaluation and expand access to high-quality cervical screening, particularly in settings where expert resources are limited.

In endometrial cancer, AI research has focused on identifying women at increased risk and exploring novel noninvasive screening modalities. ML models integrating demographic, reproductive, and metabolic variables have been developed for population-level risk prediction.[5,6] Advances in imaging also hold clinical potential with ML and DL models applied to transvaginal ultrasound images and data to improve detection of endometrial atypical hyperplasia and carcinoma.[7]

Ovarian cancer, often diagnosed at advanced stages, represents one of the most pressing challenges related to screening. AI-based models have been developed to integrate imaging, serum biomarkers, and clinical data for improved risk stratification. In a large clinical dataset,

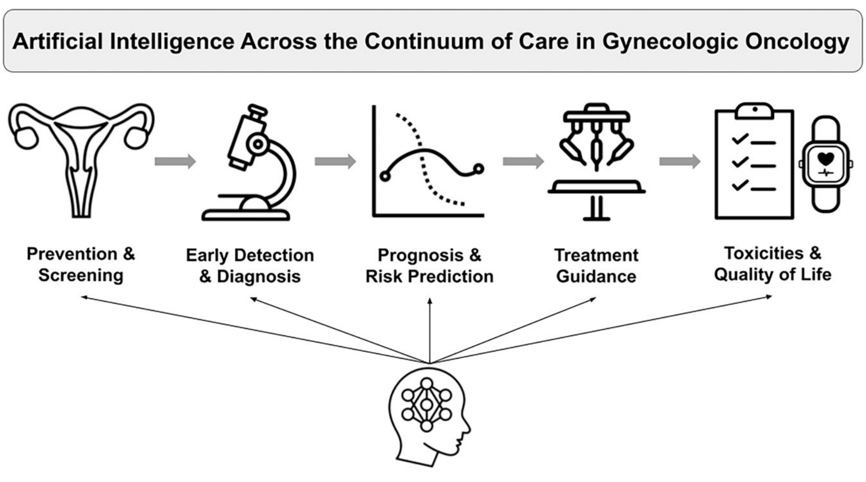

FIGURE 1. Artificial intelligence across the continuum of care in gynecologic oncology: artificial intelligence applications span every phase of gynecologic cancer care, from prevention and screening through diagnosis, prognosis, treatment guidance, and survivorship. Across each step, machine learning and deep learning models integrate multimodal data (clinical, imaging, histopathology, molecular, and patient-reported outcomes) to enhance diagnostic precision, personalize therapy, and optimize quality of life.

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Nopour et al[8] reported that an ML model achieved an AUC of 0.93 in identifying high-risk patients, highlighting the potential of AI for targeted screening. Efforts are also expanding into cell-free DNA (cfDNA)-based screening, where AI-enhanced liquid biopsy analyses can detect subtle tumor-derived signals. Studies leveraging cfDNA methylation, fragmentation, and mutation profiles augmented by DL classifiers have demonstrated encouraging accuracy for detecting ovarian among other cancer types.[9,10]

Collectively, these advances demonstrate that AI, particularly when applied in multimodal frameworks, holds significant promise for earlier and more accurate detection of gynecologic cancers with the potential to improve patient outcomes. As these tools mature, they may not only enhance precision screening and personalized prevention but also help extend equitable access to high-quality diagnostic care globally.

EARLY DETECTION AND DIAGNOSIS

AI is expected to have one of its earliest and most meaningful impacts in gynecologic oncology within the areas of early detection and diagnosis. This is largely due to the data-rich nature of radiology and pathology, which are well suited for DL model development and validation.[11] Early detection remains one of the most powerful determinants of survival across gynecologic malignancies, while accurate diagnosis is fundamental for guiding optimal treatment selection. Despite advances in diagnostic imaging and molecular pathology, traditional workflows are often indeterminate, subjective, and labor-intensive. AI-enabled tools that incorporate imaging, histopathology, clinical data, and increasingly multimodal integration are transforming how clinicians, radiologists, and pathologists approach the diagnostic process. By identifying patterns imperceptible to the human eye, AI has the potential to increase diagnostic speed, reproducibility, and precision. As these algorithms mature, they may standardize interpretation and expand access to high-quality diagnostics, particularly in resource- or expertise-limited settings.

Ultrasound remains the frontline modality for evaluating adnexal and uterine abnormalities. Deep learning models applied to grayscale and Doppler ultrasound have achieved sensitivities exceeding 90% for differentiating benign from malignant adnexal masses, often outperforming established scoring systems such as the International Ovarian Tumor Analysis (IOTA and O-RADS) models and Ovarian-Adnexal Reporting and Data System (O-RADS).[12] In a large international, multicenter validation study, an AI model outperformed experts for ovarian cancer detection.[13] DL models can even infer histologic type based on ultrasound.[14] Similar techniques can be applied to endometrial ultrasound to diagnose endometrial cancer without tissue biopsy.[7] By analyzing textural, vascular, and temporal features, these models can serve as first-line triage tools, flagging high-risk lesions for further imaging, more directed tissue biopsy, or specialist referral.

Magnetic resonance imaging (MRI) is often used to provide complementary anatomic detail when working up a gynecologic concern. Multiparametric MRI-based AI models have demonstrated strong accuracy for predicting myometrial invasion depth, cervical stromal involvement, and parametrial spread.[15] Such information is essential for fertility-sparing decision-making and for tailoring the extent of surgery or adjuvant therapy. Together with emerging positron emission tomography/computed tomography (PET/CT) applications, these applications underscore the potential for AI to enhance early recognition and diagnosis across gynecologic disease sites.

Beyond imaging, AI-enabled noninvasive assays incorporating circulating cfDNA and other multiomic biomarkers are emerging as powerful tools for early detection. Several studies have evaluated cfDNA fragmentomics and methylation-based approaches for ovarian cancer screening, demonstrating encouraging diagnostic performance in early-stage disease.[10,16] Similar fragmentomic analyses have been applied to plasma samples for early detection of endometrial cancer, identifying characteristic cfDNA fragmentation patterns with high sensitivity and specificity.[17] While still maturing toward population-level screening, these blood-based approaches that rely on AI analysis complement image-based triage and may identify candidates for targeted imaging or biopsy earlier in the disease course.

After early detection, precise diagnosis is foundational for treatment planning and prognostication. Histopathology remains the backbone of cancer diagnostics and the digitization of slides has enabled AI-assisted diagnostics in gynecologic oncology. Whole-slide imaging provides a robust platform for DL models that can identify tumor regions, classify histotype, and assign grade with reproducibility that exceeds interobserver agreement among pathologists.[18] These systems offer consistency and efficiency while preserving the interpretive oversight of pathologists. Attention heatmaps and saliency overlays enhance transparency by showing which tissue regions contribute most to the algorithm's prediction.

AI is increasingly bridging histology and molecular biology. Multiple studies have demonstrated that DL models can infer key genomic and molecular features directly from routine hematoxylin and eosin (H&E) slides. These include prediction of The Cancer Genome Atlas (TCGA)-aligned molecular subtypes of endometrial cancer[19,20] and specific molecular alterations such as microsatellite instability (MSI), mismatch repair deficiency (MMR), tumor mutational burden (TMB), TP53 mutations, and homologous recombination deficiency (HRD).[20,21] These models achieve AUCs above 0.90 compared with immunohistochemistry and genomic sequencing and have been validated across multiple institutions, suggesting they capture reproducible morphologic correlates of genotype. In practice, AI-based molecular prediction could serve as a triage mechanism to identify patients most likely to benefit from confirmatory molecular testing, reducing cost and turnaround time while maintaining diagnostic accuracy. These digital biomarkers complement established clinicopathologic factors and are emerging as important factors in guiding adjuvant therapy selection, as has been done for other cancer types (eg, prostate cancer for hormonal therapy).

Diagnostic accuracy improves further when different modalities (eg, histology, imaging, and molecular and clinical variables) are combined. Early studies have demonstrated that multimodal models outperform single-modality systems for classification and prediction. Collectively, these approaches signal a transition from pattern recognition toward biologically integrated inference, enabling clinicians to achieve more comprehensive diagnostic insight.

AI has demonstrated clear potential to enhance both early recognition and diagnostic precision in gynecologic oncology. The next step lies in the integration of these modalities into cohesive diagnostic ecosystems that deliver biologically informed, real-time decision support. Continued external validation, harmonization of data standards, and regulatory oversight will be essential to ensure safe and equitable implementation. As these tools mature, we hope for earlier detection, more accurate classification, and ultimately, more personalized treatment for patients with gynecologic cancer.

PROGNOSIS AND RISK PREDICTION

Accurate prognosis and recurrence-risk estimation are one of the most pressing challenges in clinical practice, where outcomes often diverge despite similar stage and histology. Reliable risk stratification is critical for optimizing treatment selection, tailoring surveillance strategies, and informing patient counseling. AI can be a transformative tool in this domain, with potential for better predictive accuracy over conventional statistical models and offering a pathway toward more individualized, data-driven management.

In cervical cancer, a multicenter, multimodal AI model was developed to predict overall survival and recurrence.[22] Similarly, in endometrial cancer, AI has been shown to substantially advance recurrence and survival prediction and improve risk stratification. Miller et al[23] developed an integrated prediction model for recurrence of endometrioid endometrial cancers, combining clinical, pathologic, and molecular features to identify high-risk patients. Gonzalez-Bosquet et al[24] built upon this work by integrating genomic data, including RNA sequencing-derived features to accurately predict recurrence, outperforming models using only clinical characteristics, and was validated in an independent TCGA cohort. Expanding this work using the ORIEN multi-institutional database, investigators used AI models integrating clinical, molecular, and genomic data in low-risk, high-risk, and nonendometrioid groups to predict recurrence, outperforming clinical and TCGA molecular surrogate models.[25] A notable advance is HECTOR, a multimodal model integrating whole slide images and clinical data from endometrial cancer patients in the PORTEC trials. HECTOR outperformed conventional pathology-based predictors and accurately estimated 10-year distant recurrence-free survival in low-risk patients with 97% accuracy.[26]

In ovarian cancer, predicting recurrence and survival is critical for risk management. Ma et al[27] showed that surgical findings can be highly prognostic when captured systematically with laparoscope and analyzed with DL to predict treatment outcomes. Mysona et al[28] introduced ORACLE score, a model integrating serum proteomics and clinical variables, which stratified recurrence risk more accurately than CA-125 alone, identifying high-risk patients despite normal CA-125. Other AI-enabled prognostic approaches leverage clinical factors, gene mutation profiles,[29] and imaging features,[30] collectively demonstrating the value of multimodal integration for individualized outcome prediction.

Together, these studies illustrate the rapidly expanding role of AI in prognostic modeling across gynecologic cancers. By integrating multimodal data (clinical, imaging, histopathology, and genomics) AI models consistently outperform conventional approaches. As model interpretability, external validation, and integration into clinical workflows improve, AI-driven prognostic tools are poised to enable personalized surveillance and treatment planning, improving outcomes while minimizing overtreatment.

TREATMENT GUIDANCE

AI is increasingly being evaluated for integration into the therapeutic decision-making process in gynecologic cancers. This application extends AI beyond diagnostics toward clinical decision support, operative guidance, and treatment delivery. Because cancer care is inherently multimodal spanning surgery, radiation, and systemic therapy, AI's greatest potential is in improving precision and personalization of complex treatment decisions.

AI-driven decision support tools are being developed to help ensure treatment choices align with established guidelines and to identify situations where management deviates from standard recommendations. Large language models and predictive algorithms trained on structured clinical data can rapidly synthesize patient-specific information, summarize evidence, and propose guideline-based options.[31] However, early evaluations of generative AI systems, such as those comparing ChatGPT with national treatment guidelines, highlight both the promise and the current limitations of these technologies. These models can assist with education and documentation but are not yet reliable for autonomous decision-making. As clinical decision support matures, it will likely take the form of integrated "human-in-the-loop" systems—offering recommendations grounded in National Comprehensive Cancer Network (NCCN) or European Society of Gynaecological Oncology (ESGO) guidelines while retaining clinician oversight and responsibility.[32]

Surgery represents an area where AI can directly influence both operative planning and intraoperative decision-making. Several groups have developed models that integrate clinical, imaging, and genomic data to guide surgical strategy in ovarian and endometrial cancer. Multiple studies have evaluated AI to predict the likelihood of optimal cytoreduction in patients undergoing debulking surgery for advanced ovarian cancer. These predictive tools use diverse data types, including imaging, clinical, and genomic and can assist with preoperative counseling, resource allocation, and referral to high-volume centers.[33–35] Other AI tools can preoperatively stratify endometrial and cervical cancer risk for nodal metastasis, potentially influencing surgical planning or nodal assessment techniques.[36] Intraoperatively, advances in imaging, augmented reality, and computer vision are being combined with AI to delineate critical structures, highlight disease extent, and assist with navigation. These tools have the potential to standardize surgical assessment, reduce variability between surgeons, and improve safety. Collectively, these studies illustrate how AI can inform not only who should undergo surgery, but also how surgery should be approached. Furthermore, AI-based tools can be used to predict perioperative complications, ICU stay, and length of stay, enabling better perioperative planning and risk mitigation.[37,38]

Robotic platforms provide a unique environment for real-time data capture and algorithmic assistance. There are many emerging applications, including automated camera control, gesture recognition, and performance analytics to provide objective feedback and skill assessment.[39] While fully autonomous surgery remains speculative, these incremental innovations are realistic near-term steps. Importantly, such systems must undergo rigorous validation and operate under explicit human supervision to maintain safety and trust.

An exciting application of AI in gynecologic oncology lies in systemic treatment selection. Predictive models are being developed to identify which patients are most likely to respond to chemotherapy, immunotherapy, or targeted therapy by integrating histopathologic, molecular, and clinical data. These efforts reflect a broader shift toward response-predictive modeling rather than simple prognostication.

DL applied to routine histology has revealed that treatment-relevant information such as platinum sensitivity or homologous recombination deficiency can be extracted directly from slides.[21,40] Similarly, multimodal algorithms that combine pathology, proteomics, and genomic profiles have demonstrated improved accuracy over single-data-type models.[41,42] This approach mirrors the molecular evolution of gynecologic oncology itself, where subtype classification has replaced traditional histologic categories as the foundation for treatment decisions.

In practice, these tools could enable a more individualized approach to systemic therapy, identifying patients who would benefit from neoadjuvant chemotherapy versus upfront surgery, predicting which tumors are likely to respond to specific therapeutics and guiding enrollment into data-driven clinical trials. While these applications remain largely investigational, they represent a clear trajectory toward AI-enabled precision therapeutics that move beyond single biomarkers to integrated, data-driven signatures of response.

AI also offers an opportunity to modernize how patients are identified and enrolled in clinical trials. Trial eligibility screening remains one of the most resource-intensive and error-prone steps in research, often relying on manual chart review. NLP systems can now parse electronic health records, pathology reports, and molecular results to automatically match patients with open studies, flagging potential candidates for investigator review.[43] Beyond logistics, AI can also support trial enrichment, helping design studies that preferentially enroll patients most likely to benefit based on complex, multimodal biomarkers. Such approaches could accelerate accrual, improve trial efficiency, and make study populations more representative and equitable.

Just as molecular classification transformed how we think about endometrial cancer, AI has the potential to redefine how we guide treatment across all gynecologic malignancies. The goal is not to automate decisions, but to augment the precision, consistency, and equity of the care available to our patients.

TOXICITIES AND QUALITY OF LIFE

Treatment-related toxicity is an important determinant of long-term outcomes and quality of life in patients with gynecologic cancers. There is a persistent need for predictive tools that anticipate adverse effects, guide symptom management, and preserve well-being throughout and beyond treatment. AI can be used to integrate clinical, dosimetric, imaging, and patient-reported data to model toxicity risk and support precision symptom monitoring.

AI models have demonstrated value in predicting radiation- and chemotherapy-associated complications. Portocarrero-Bonifaz et al[44] demonstrated the utility of machine learning models to predict severe toxicity in patients receiving radiation with brachytherapy using dosimetric and clinical parameters. Similarly, Finkelstein et al[45] applied DL to longitudinal symptom trajectories during chemotherapy, finding that early electronic symptom data could forecast later toxicities and enable proactive management. Together, these studies illustrate how AI can shift toxicity management from reactive to anticipatory care.

Despite this progress, there is limited research on the application of AI to patient-reported outcomes in gynecology oncology. Future research should prioritize combining clinical, physiological, and patient-reported data into interpretable, validated frameworks that can identify patients at highest risk for toxicity while preserving patient autonomy and well-being. These early advances highlight AI's potential to extend beyond treatment decision-making into quality of life, where its ability to integrate multimodal data may transform long-term monitoring, toxicity mitigation, and individualized follow-up strategies for gynecologic cancer survivors.

IMPLEMENTATION CHALLENGES AND ETHICAL CONSIDERATIONS

Successful translation of artificial intelligence into gynecologic oncology practice requires careful attention to data quality, model interpretability, regulatory oversight, and equitable implementation. These considerations are essential to ensure that AI improves rather than amplifies existing disparities in cancer care.

The performance of AI models depends heavily on the diversity and representativeness of training datasets. Gynecologic oncology datasets are often small, institution-specific, and lack racial, socioeconomic, or geographic diversity, raising concerns about generalizability and algorithmic bias. Historical data imbalances can inadvertently perpetuate disparities in diagnosis and outcomes, particularly for underrepresented populations.[46] Mitigation strategies include rigorous external validation, subgroup performance reporting, and bias auditing before deployment. Developing multi-institutional and international collaborations can further improve data heterogeneity and enhance fairness across diverse patient populations.

While DL models often achieve high accuracy, their "black-box" nature remains a major barrier to clinical adoption. Explainable AI techniques such as saliency maps, feature attribution, and attention-based visualization can help clinicians understand the model's decision process.[47] However, these post hoc explanations are not always reliable, and there is growing emphasis on inherently interpretable or hybrid modeling approaches that align with clinical reasoning.[47] Transparent reporting frameworks such as TRIPOD-AI and CONSORT-AI are increasingly required to promote reproducibility, interpretability, and regulatory acceptance.

AI models used for diagnosis, prognosis, or treatment guidance are considered high-risk medical devices by regulatory authorities. The US Food and Drug Administration (FDA) has established an evolving framework for AI/ML-based Software as a Medical Device (SaMD) emphasizing real-world performance monitoring, lifecycle

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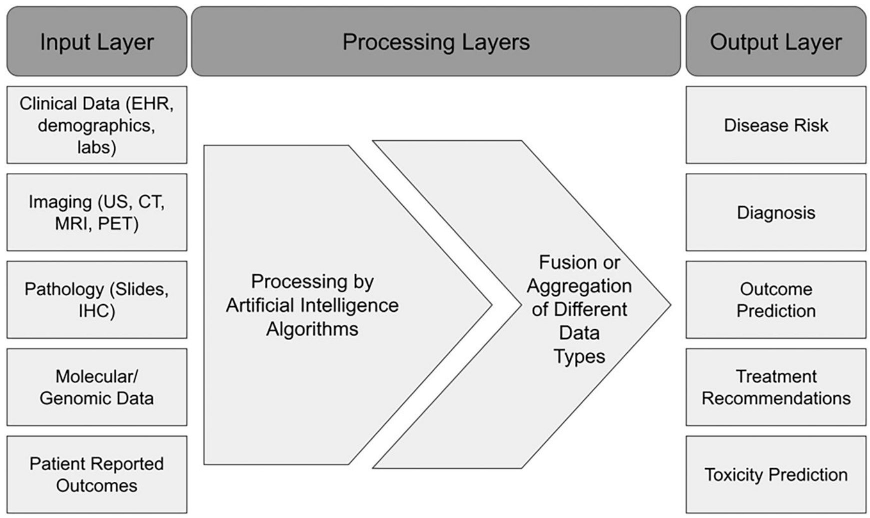

FIGURE 2. Multimodal artificial intelligence framework for precision gynecologic oncology: conceptual overview of multimodal artificial intelligence (AI) architectures used in gynecologic oncology. Input data, including clinical variables from the electronic health record (EHR), imaging, pathology slides and immunohistochemistry (IHC), molecular/genomic information, and patient-reported outcomes, are processed through specialized encoders and integrated in a fusion layer to generate outputs such as disease risk, diagnosis, treatment recommendations, and toxicity prediction. This framework illustrates how AI systems can unify heterogeneous data streams to enable precision medicine.

oversight, and "Predetermined Change Control Plans" to govern adaptive algorithms. In parallel, the European Union's AI Act mandates strict requirements for transparency, human oversight, and data quality in high-risk medical AI systems. Beyond regulation, protecting patient privacy is paramount. Conventional de-identification is often insufficient when combining imaging, molecular, and clinical data. Federated learning (FL) has emerged as a promising paradigm that enables model training across multiple institutions without direct data sharing. These decentralized frameworks maintain data sovereignty while allowing for robust multisite validation, though challenges remain around standardization, data harmonization, and secure aggregation.

The clinical utility of AI must ultimately be measured not only by accuracy but also by its impact on outcomes, efficiency, and cost. Cost-effectiveness analyses are still limited, yet preliminary evidence suggests that AI-assisted radiology and pathology workflows can improve diagnostic turnaround time and reduce unnecessary procedures. Implementation research should focus on quantifying these benefits and identifying potential unintended consequences. Moreover, equitable access to AI technologies is essential to avoid deepening global disparities. Cloud-based and mobile AI solutions offer opportunities to extend expertise into low-resource settings, provided they are accompanied by sustainable infrastructure and culturally appropriate deployment strategies.

The rapid expansion of AI also raises environmental concerns, as training large models consumes significant energy and water resources. Efficient model architectures, shared compute infrastructures, and renewable energy sourcing represent important steps toward sustainable AI in health care. Ethical implementation further requires maintaining clinician oversight, ensuring informed consent for data use, and embedding mechanisms for accountability and postdeployment auditing.

Collectively, addressing these technical, ethical, and societal challenges will determine whether AI becomes a true equalizer in gynecologic oncology or reinforces existing barriers to care.

FUTURE DIRECTIONS

The study of AI in gynecologic oncology is evolving rapidly, moving from proof-of-concept algorithms toward integrated clinical systems capable of informing prevention, diagnosis, and treatment decisions across the continuum of care.

Foundation models trained on massive datasets across domains (text, imaging, genomics, and histopathology) are reshaping medical AI. In both pathology and radiology, large-scale models have demonstrated near-universal representations that generalize across cancer types and institutions. The next frontier involves multimodal architectures that integrate histology, radiology, genomics, and electronic health record (EHR) data creating holistic patient representations capable of capturing both biology and clinical context.[48] For gynecologic oncology, such systems could unify diverse data streams to predict disease trajectory, treatment response, and survivorship outcomes with unprecedented precision (Fig. 2).

Clinical integration will require interoperability, transparency, and trust. Embedding AI models into existing electronic medical record systems through standardized interfaces that can facilitate real-time decision support. Explainable outputs, accompanied by uncertainty estimates and links to supporting evidence, are essential to ensure clinician confidence and patient safety. Prospective implementation studies, human factors research, and feedback mechanisms will help optimize how AI tools are used in daily workflows. These strategies align with "human-in-the-loop" paradigms where AI augments, rather than replaces, clinical judgment.

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Ultimately, the success of AI will be measured not by AUCs but by clinical benefit. Future research should emphasize prospective trials, implementation studies, and postdeployment monitoring to quantify AI's effects on patient outcomes, cost, and equity. Equally important will be education and upskilling of the oncology workforce to ensure clinicians can critically evaluate, interpret, and safely apply AI outputs in patient care. AI has already begun transforming how we detect, diagnose, and manage gynecologic cancers. The next era will focus on integration, interpretation, and equity to ensure these technologies become reliable partners in delivering truly personalized, high-quality cancer care worldwide.

CONCLUSION

AI is redefining what is possible in gynecologic oncology by linking prevention, diagnosis, treatment, and survivorship into a connected continuum of precision care. Multimodal AI systems that integrate clinical, imaging, molecular, and patient-reported data are beginning to reveal patterns that were once unknown, enabling earlier detection, individualized therapy, and dynamic monitoring. Beyond performance metrics, the true promise of AI lies in its capacity to extend expertise, reduce inequities, and learn continuously from every patient encounter.

The next phase of progress will depend on collaboration: diverse datasets, transparent validation, prospective evaluation against current methods, adaptive regulatory frameworks, and workforce education that empowers clinicians to partner with these technologies responsibly. Together, these advances may ultimately fulfill the promise of precision oncology in gynecologic cancers, characterized not only by technological sophistication, but by genuinely personalized care and improved outcomes for every patient.

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