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Advancing Cervical Cancer Management with Artificial Intelligence: Current Perspectives and Future Trends

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Abstract

Background: The field of cervical cancer care has been revolutionized by artificial intelligence (AI), enabling advanced analysis of imaging and multi-omics data, and leading to more accurate diagnosis, improved prediction of patient outcomes, and support for personalized treatments.

Procedure: This systematic review complies with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) and uses the PRISMA checklist. A comprehensive literature search was conducted using the databases of Web of Science, Scopus, IEEE, and PubMed to identify the characteristics of studies published between 2021 and 2026. Published literature were assessed for eligibility as long-form (original and review articles) relating to AI use for screening, diagnosis, prognosis, radiomics, pathology, and clinical decision support in relation to cervical cancer. All data synthesized were qualitative.

Results: AI-based models enable accurate identification and classification of cervical neoplasia. They also facilitate earlier diagnosis through automated feature extraction from imaging. AI-assisted frameworks are beginning to support the development of precision medicine treatments tailored to individuals.

Discussion: The clinical translation of AI into practice faces challenges such as data heterogeneity, insufficient external validation, and a lack of model interpretability. To address these, creating standardized datasets and developing interdisciplinary collaborations will enhance AI adoption in clinical practice.

Conclusion: There is substantial potential for AI to provide improved cervical cancer care. Future initiatives to facilitate this include creating well-validated, standardized datasets and

clinically interpretable models to ensure the successful implementation of AI in practice in the real world.

Keywords

Artificial intelligence; Cervical cancer; Machine learning; Deep learning; Clinical decision support..

1. Introduction

There were 660,000 new cases of this tumour diagnosed worldwide in 2022, with 350,000 resulting in death [1]. This ranked the tumour as the 4th most common cancer diagnosis, and the 4th leading cause of cancer death in females. It is still possible to eradicate this type of solid tumour if comprehensive prevention programs are implemented, such as widespread use of the 9-valent HPV vaccine, screening of the entire population, and starting treatment on time [2]. Persistent infection with high-risk HPV genotypes (approximately 15 oncogenic strains) is an essential etiological factor in cervical carcinogenesis [3]. The disease follows a specific path: it starts with an infection in the transformation zone, then the virus stays in the body thanks to immune-evasive mechanisms, then it evolves into high-grade CIN through E6/E7-mediated inactivation of p53 and Rb, and finally it breaks through the basement membrane, leading to invasive carcinoma [4]. Despite the demonstrative effectiveness of HPV vaccination, vaccine uptake is still sub-optimal among individuals and, more importantly, a majority of programs center on individuals less than 26 years of age in even the wealthiest areas of the globe [5]. Vaccinated populations are still advised to continue normal protocol for cervical screening due to the continued risk for infection and breakthrough disease [6]. To reduce the global burden of cervical cancer, expanding coverage of vaccines, ensuring that screening programs have equal access, and strengthening implementation approaches will be of utmost importance [7]. All these efforts are necessary to improve cervical cancer survival and reduce the incidence of this disease, screening at the population level, prompt evaluation of symptoms, and clinical intervention are necessary [8]. Cervical cancer remains highly treatable when detected early, despite barriers to successful implementation [9]. Even though new diagnostic technologies have enhanced early detection, there are still several drawbacks to a precise and consistent diagnosis among the experts, such as differences in opinion, varying quality in health care resources, and the nature of the tumors [10]. However, clinical adoption remains limited [11]. Although LLMs perform reliably (>90% accuracy) on general prevention and awareness tasks, their accuracy declines with complex diagnostic and therapeutic decision-making, with risks of hallucination and guideline deviation [12].

2. Methodology

For technology, we used 'artificial intelligence,' 'machine learning,' 'deep learning,' and 'neural networks.' Searches were conducted across four databases: PubMed, Web of Science, Scopus, and IEEE Xplore. We included only English-language studies published between 2021

Table 1: Advanced comparative overview of traditional ML, deep learning, and generative AI in cervical cancer research.

Dimension	Traditional Machine Learning (ML)	Deep Learning (DL)	Generative AI (GAI)	References
Data Dependency	Performs best with structured and curated datasets; model quality depends heavily on expert-defined features.	Requires large, annotated datasets (especially imaging); automatically extracts complex spatial and contextual patterns.	Can leverage unlabeled datasets; augments limited data via synthetic generation and enhances feature diversity.	[13]
Strengths	High interpretability; efficient training; low computational demand; robust on small structured datasets.	Superior performance in image/audio/sequence tasks; end-to-end learning; strong generalization for complex multimodal data.	Enables simulation & synthetic dataset expansion; mitigates class imbalance; enhances privacy by generating non-identifiable patient data.	[14]
Computational Paradigm	Learns predictive rules from engineered feature sets using classical algorithms.	Hierarchical representation learning using multi-layer neural networks (e.g., CNNs, Transformers, LSTMs).	Learns high-dimensional data distributions to synthesize novel samples or latent representations (e.g., GANs, VAEs, diffusion models).	[15]
Key Biomedical Applications	Risk stratification, biomarker-based classification, clinical parameter-driven predictive modeling.	Automated cytology & colposcopy interpretation, lesion segmentation, radiomic and pathomic feature learning.	Synthetic cervical cytology images, segmentation mask generation, stain normalization, data augmentation for low-resource environments.	[16]
Role in Cervical Cancer AI Ecosystem	Baseline clinical decision support (risk scoring, survival modeling).	Primary engine for automated diagnostic pipelines.	Data augmentation and simulation layer bolstering ML/DL workflows and training.	[17]
Limitations	Limited capacity for complex nonlinear feature discovery; requires domain expertise for feature engineering.	Computationally intensive; demands extensive GPU resources; limited transparency ("black-box" nature).	Risk of producing unrealistic outputs; potential hallucination/overfitting to training distribution; ethical concerns for synthetic patient data.	[18]

and 2026. To ensure methodological transparency and reproducibility, the review followed PRISMA guidelines. Different structural syntax was used for each database. In addition, the references of all eligible studies identified were manually screened to locate any additional

pertinent publications. A study had to meet all criteria to be eligible: specifically discuss cervical cancer, apply either artificial intelligence or machine learning, and include at least one clinical or translational application (screening, diagnosis, prognosis, treatment planning, outcome prediction, pathology, radiomics, and clinical decision support) published as either an original research or a review article in a peer-reviewed journal. Cervical cancer studies were excluded if they did not relate directly to cervical cancer, included generalized gynecologic cancers without separate analysis of cervical cancers, were only focused on the development of an algorithm (technical) without any type of biomedical or clinical applicability, were editorials/letters/conference abstracts that were not available to be reviewed in full text or were not accessible to reviewers in full text. Disagreements related to eligibility were resolved through the cooperation of all authors. For each of the selected studies, data of interest were extracted, including the clinical task (assessed via diagnostic accuracy), data modality, AI method used, validation method used, performance measure(s), and clinical applicability of results, as well as synthesizing results quantitatively using themed categories. The stages of the study selection process (identification, screening, determining eligibility, and accepting/excluding studies) have been documented through the creation of a PRISMA flow diagram to ensure a transparent and reproducible review of the current state, challenges, and opportunities for future work in AI related to cervical cancer management (Fig.1).

3. Results

3.1. Applications of AI/ML in Cervical Cancer Management

3.3.1. Screening and Early Detection

Computer vision techniques for automatic and automatic analysis of pap smears, along with other traditional methods, are becoming more prevalent within the context of cervical cytology (Paps) or imaging alternatives [19]. In addition to increasing adoption rates of computer vision technology, several studies have demonstrated the efficacy of using deep convolutional neural networks (CNN's) in assessing digitized versions of pap and cervigraphic artwork (full slide images). In addition, other studies have indicated that deep convolutional neural networks can accurately retrieve and evaluate cytologically classified pap abnormal pap smears as well as cervical intraepithelial (CIN) lesions from digitizing WSI's at a very high sensitivity and positive predictive value (PPV) [20]. Supporting the notion of contrastive pre-training, recent studies revealed that models initialized with SimCLR are capable of accurately classifying HPV-positive cytology samples, regardless of limited annotation availability and underlining the translational capacity of self-supervised representation learning into cervical cancer screening workflows [21].

In addition to developments in cyto-automation, AI-enabled mobile health (mHealth) applications are being used to expand screening structures in low-resource settings where traditional cytology and HPV testing cannot logistically be performed [22]. MHealth cervicography applications for smartphones with embedded deep learning algorithms now allow point-of-care visual inspection with acetic acid (VIA) so that frontline clinicians and, in

some settings, patients can capture and examine cervical images in real-time [23]. A novel Android-based VIA application was used to take pictures of the cervix before and after an acetic acid wash and had ~94% diagnostic accuracy during field testing, demonstrating its promise for decentralized screening [24]. Handheld imaging with automated trinage has also shown increased coverage and immediate linkage to cryotherapy, helping to support the WHO's single-visit "screen-and-treat" model for early management of cervical disease [25].

At the same time, large language models (LLMs) are actively being evaluated as clinical decision-support tools that can absorb electronic questionnaires and structured/unstructured patient information to discern values of important risk modifiers (e.g., sexual behavior, tobacco exposure, immunosuppression), in order to enhance automated risk stratification and clinical decision support [26]. Initial findings suggest LLM-supported triage systems can autonomously build complete patient history, effectively request missing risk factors, and alleviate clinician burden [27]. New multimodal architectures that combine LLM-encoded clinical context with AI-based cervicographic feature extraction have shown potential in improving the rigor of diagnostic capacity [28].

3.3.2. Diagnosis and Histopathological Evaluation

Machine learning (ML) has greatly advanced computational diagnostics in cervical cancer, specifically in cytology, colposcopy, histopathology, and magnetic resonance imaging (MRI) [29]. A study reported that a combined autoencoder-CNN model produced an accuracy of 96.54% on SurePath Pap smears, which indicated improved performance over standardized cytologic interpretation that would entail further examination by a pathologist; however, the model did not perform well in comparison to cytology for thin prep specimens, indicating the need for algorithms to be trained on domain-specific annotation [30]. Therefore, transfer learning strategies based on domain-adaptive learning methods improved performance from the first dataset to the second dataset, including a restructured ResNet101 architecture that attained an accuracy of 92.65% following adaptation [31]. AI-enabled radiomics similarly advanced the characterization of tumors on MRI. A multiparametric MRI model using dynamic contrast-enhanced T1-weighted images and T2-weighted images to develop a model to discriminate between invasive tumor patterns obtained an AUC of 0.911, indicating a strong radiologic biomarker potential for graduate-level tumor histopathology in women with cervical cancer [32].

Classical ML techniques—like decision trees, logistic regression, support vector machines (SVMs), learners—are also exceptionally predictive; when evaluated, AdaBoost, and classifiers achieved 100% accuracy, while SVMs achieved 99% accuracy [33]. Additionally, survey research with 132 participants in Saudi Arabia revealed high public receptivity to AI-based cervical cancer prediction systems and HPV-risk awareness programs [34]. State-of-the-art ML-based predictive models in cervical cancer research are summarized in Table 2 (including models, clinical endpoints, and associated metrics) [35-45], emphasizing rapid methodological development and increasing translational value.

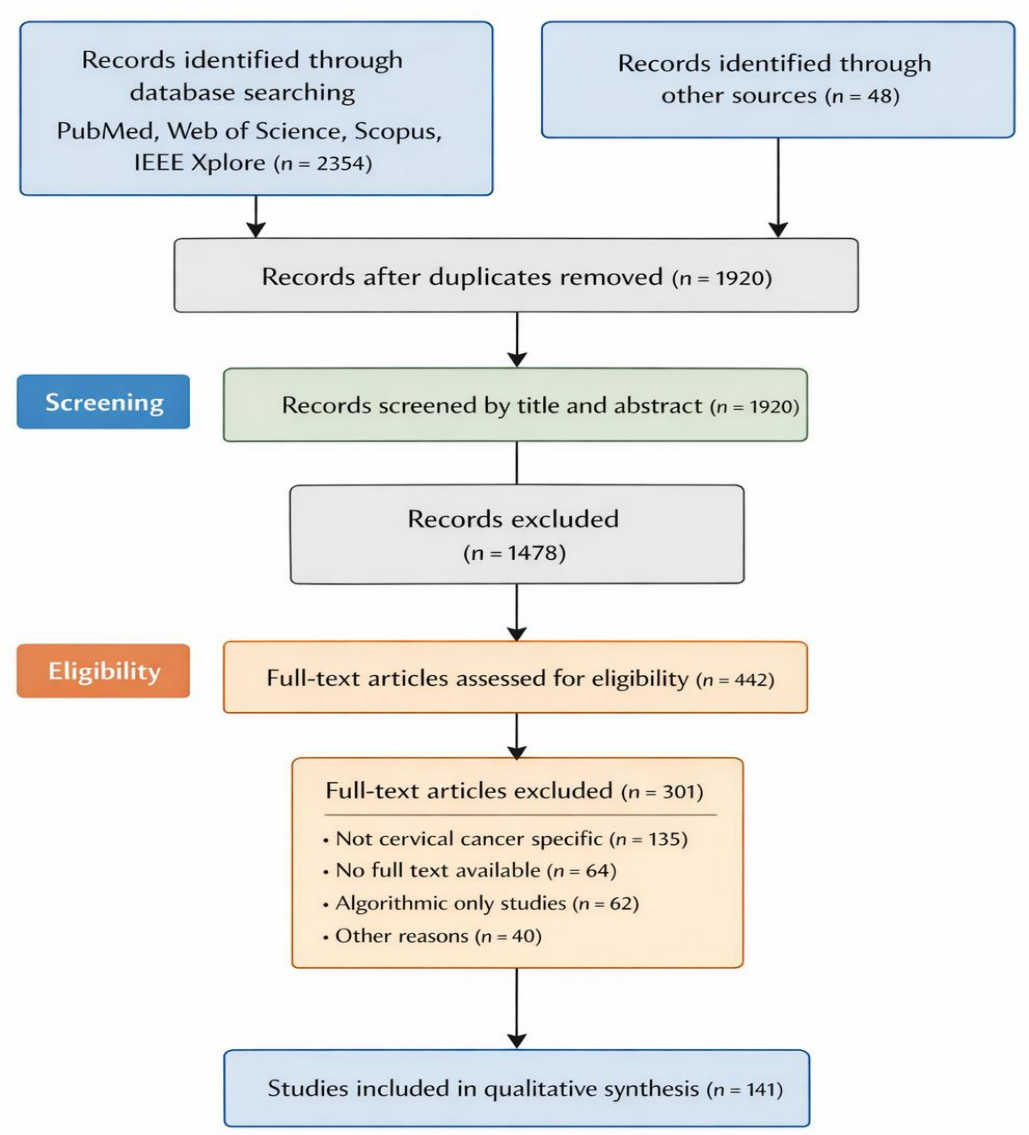

Figure 1. The flow diagram illustrates the selection process of studies included in the review, following the PRISMA 2020 guidelines.

Table 2. Advanced Machine Learning Models in Cervical Cancer Research.

Study / Year	Wang et al. (2024)	Li et al. (2024)	Akash et al. (2024)	Ji et al. (2024)	Zhao et al. (2024)	Karamti et al. (2023)	Liu et al. (2023)	Kang et al. (2023)	Xiao et al. (2023)	Zhang et al. (2023)	Abdalvand et al. (2022)
Cohort & Data	223 retrospective + 58 prospective	472 pts (clinical + SNPs)	SiPaKMeD dataset	1.7 M screened cases	236 retrospective	Pap smear dataset	180 MRI + clinical	Raman tissue spectra	21,720 HPV + women	218 RT plans (59 pts)	111 LACC cases
Primary Focus	Stage, histology, grade, LNM prediction	Early cancer/precancer risk	Cell classification & cervix type (CerviXpert)	Population AI screening	Predict LNM	Class-imbalance handling	Predict LNM	Spectroscopy-based detection	CIN2+/CIN3+ risk modeling	OAR dose prediction	Brachytherapy response
Techniques Used	Multi-task ANN	LR, SVM, RF, DT, XGB, ANN	Multi-branch CNN	Cloud-AI system	RF, SVM, XGB, etc.	KNN-SMOTE + Ensemble	Radiomics + ML	CNN + ResNet	Stacked Ensemble	Neural Network Regression	LASSO, SVM, RF
Performance Metrics	Accuracy, F1	ROC, DCA	Accuracy (5-fold CV)	Coverage, Cost, Speed	AUC, Accuracy, Sens., Spec., F1	Acc, Precision, Recall, F1	AUC, Sens., Spec., Acc	Acc, Recall, F1, AUC	AUROC, Sens., Spec., LR	R, MSE, ΔD2cc/D90	AUC, Sens., Spec., Acc
Key Findings	Multi-task > clinicians (except LNM)	6-SNP LR model most effective	98% + accuracy; > MobileNetV2/InceptionV3	87× speed; low-cost deployment	RF best (AUC 0.91/0.85)	99.99% classification	NB best AUC (0.745); spec 0.90	94% Acc, 96.86% AUC	AUROC ↑ ~40%; LMIC utility	High OAR correlation	RF AUC 0.82 > LR

3.3.3. Treatment personalization

Radiotherapy will still be a major component for patients with locally advanced disease, conventional planning requires substantial manpower, is reliant on the planner's experience, and remains subjective based on the techniques and heuristics used by individual planners [46]. Artificial intelligence provides a scalable method for challenging dosimetric tasks presented in a clinical workflow while providing precision and consistency [47]. Generative deep-learning systems, particularly generative adversarial networks (GANs), have shown strong capabilities in creating patient-specific three-dimensional dose distributions directly from CT anatomy and tumor delineations, producing clinically-sync conformal plans with considerably less manual planning [48]. For example, DosimetryGAN replicates previously validated patients' dose prescriptions accuracy, and Beam-path GAN (Bc-GAN) extends this by accurately generating plans to match multi-beam geometries while maintaining robust output across varying delivery scenarios [49].

These models consistently outperform traditional planning workflows by decreasing dose-prediction error and greatly reducing treatment-planning duration, and they generalize sufficiently well across radiotherapy modalities when trained on datasets of IMRT and VMAT [50]. This presents a clear advantage in the field of adaptive radiotherapy, where the plan can be updated almost in real-time and increases the plan's resilience to anatomical change [51]. The use of artificial intelligence in oncologic workflows is changing the landscape of precision treatment planning in cervical cancer through the use of other advanced (LLMs) as decision-support tools [52]. While standard therapeutic selection options depend on reviewing several evidence-based consensus guidelines to determine chemoradiotherapy with treatment options or targeted approaches attributable to the clinical situation [53]. LLMs may be scaled to enhance clinical judgement by rapidly retrieving, contextualizing, and summarizing recommendations that are concordant with guidelines to fit a specific patient scenario; thus, there is potential to expedite and enhance the deliberation of treatment options [54]. Recent evaluations show that systems that are based on GPT-4 have high overall concordance to NCCN-directed therapeutic options across a variety of malignancies, including ~87% concordance in urologic cancers relative to earlier systems [55]. Within the cervical cancer pathways, these systems can systematically search for NCCN-based management strategies for clinical states (e.g., selecting treatments for IB2 disease or systemic regimens using preferred agents), thus serving clinicians' clinical judgement and multidisciplinary tumor boards in the treatment discussions [56]. Further, LLMs, connected to the electronic health record (EHR), can systematically interrogate longitudinal clinical data to identify co-morbidities, drug exposures, and precision-oncology eligibility criteria to inform and drive individualized treatments and conversations, to minimize safety or unanticipated adverse events [57].

AI-enabled pharmacovigilance applications provide additional layers of therapeutic safety. Recent literature suggests that GPT-based medication-screening frameworks can effectively identify clinically significant drug-drug interactions, including high-risk combinations occurring in patients proposed to receive concurrent chemotherapy (anticoagulation, antivirals, analgesics) - referring to work in [58]. For example, a recent ChatGPT-assisted

review was shown to identify actionable interactions with ~95% accuracy in polypharmacy settings, exemplifying one way AI may prevent adverse pharmacologic events, such as warfarin-chemotherapy conflicts [59]. Beyond drug safety, multi-modal formulations of LLMs designed to include supported references to radiotherapy dosimetric profiles, genomic markers (e.g., BRCA or HPV-associated genomic alterations), and psychosocial determinants of care are all emerging [60]. These applications will advance the specificity of context-centric approaches to therapeutic recommendations [61]. The next frontier will be a new grid AI-enabled "virtual tumor board" that may synthesize radiologic, histopathologic, electronic health record, and literature streams of evidence to help coordinate adaptive and guideline allowable treatment decisions, including radiation-treatment plans [62].

3.2. Genomic Data and AI in Cervical Cancer Prognosis

Multi-omics strategies driven by artificial intelligence are competent at estimating clinical consequences for women with cervical cancer. Employing combined multi-omics prototypes composed of somatic mutation profiling, mRNA expression marks, and protein biomarker information occurred in higher precision for projecting the prognostication of women being managed for cervical cancer and the proficiency to enhance the identification of which women are most at uncertainty for cancer reiteration or condition deterioration when analyzed using isolated single omic analyses [63]. By using multi-omics data, AI-authorized pipelines can amplify precision oncology by taking advantage of targeted molecular profiles to examine threats and the specific kind of intervention needed for each respective patient [64] (Table 3).

Table 3: Multi-Omics Biomarkers in Cervical Cancer and Their Clinical Significance.

Biomarker / Signature	Omics Layer	Biological Role / Mechanism	Clinical Relevance	AI/ML Utility	References
PIK3CA mutations	Genomics	Activates PI3K/AKT oncogenic signaling; enhances proliferative & survival pathways	Associated with aggressive phenotypes & resistance to targeted therapy	Feature in ML prognostic and therapeutic response models	[65]
TP53 alterations	Genomics	Disrupts genomic integrity and apoptosis control	Correlates with high-grade lesions and unfavorable prognosis	Integrated into AI-driven mutation-based survival prediction workflows	[66]
HPV E6/E7 oncogene expression	Transcriptomics (viral)	Inactivates p53/Rb; drives malignant transformation	Key determinant of HPV-driven carcinogenesis	Used in AI models for HPV lesion classification	[67]

				and early detection	
PD-L1 / CTLA-4	Transcriptomics / Proteomics	Mediates immune evasion within tumor microenvironment	Predicts immunotherapy response	AI in immune-landscape modeling & immunotherapy prediction tools	[68]
MMP2 / MMP9	Transcriptomics / Proteomics	Facilitates extracellular matrix degradation; metastasis promoter	Indicative of invasive potential and metastatic risk	Used in ML models assessing metastasis propensity	[69]
CXCL10 / CXCL11	Transcriptomics / Proteomics	Chemokine-mediated immune cell recruitment	Biomarker for tumor immune state and inflammatory phenotype	AI-based tumor microenvironment stratification	[70]
HOTAIR / MALAT1 (lncRNAs)	Epigenomics / Transcriptomics	Regulates EMT, chromatin dynamics & metastatic progression	Predictive of recurrence and therapy resistance	Deep-learning RNA signature modeling	[71]
miR-21 / miR-34a	Epigenomics / Transcriptomics	Post-transcriptional gene silencing affecting apoptosis & proliferation	Prognostic for recurrence and chemoresistance	AI-integrated miRNA panels for survival modeling	[72]
p16INK4a / Ki-67	Proteomics / IHC	Cell-cycle dysregulation and proliferative index marker	Gold-standard cytology biomarkers	Automated AI scoring and grading pipelines	[73]
Serine/Glycine metabolic pathways	Metabolomics	Supports proliferative metabolic reprogramming	Associated with tumor aggressiveness and metabolic subtype	Multi-omics metabolic profiling with DL frameworks	[74]

3.3. Clinical application cases of AI in large-scale cervical cancer screening

While traditional AI-enabled cervical cancer screening systems have primarily been developed and evaluated based on retrospective datasets with limited prospective validation, actual deployment in real-world settings is a necessary step before demonstrating clinical utility and impact at the population level. To address this challenge, several large prospective implementations have recently demonstrated the feasibility, accuracy, and scalability of AI-enabled cervical cancer screening programs in a variety of geographic settings. Between 2017 and 2021, a landmark population-based screening program in Hubei Province, China, screened 1,474,788 women utilizing AI-enabled cervical cytology [75]. After trained clinicians collected and prepared specimens, AI algorithms pre-scanned slides for cytological

abnormalities, cytopathologists verified positive results, and when the possibility of a negative slide being incorrectly classified was determined, random audits of negatives were conducted for high-quality assurance. It took approximately 2 minutes to scan and 1.5 minutes for a diagnosis to be made on each sample, with rapid results being utilized by proposing a digital means. This system demonstrated excellent diagnostic efficiency, diagnostic accuracy, and low cost to screen each specimen (USD ≈ 6.31), which is beneficial for deployment in medically underserved rural settings, and even potentially scalable nationally and globally

In a related investigation, Bao et al. [76] examined more than 700,000 women utilizing AI-based cytology in the same province (2017-2018). Moreover, economic analysis showed that AI semi-automated liquid-based cytology (LBC) every five years was more cost-effective than standard manual testing, indicating viability for sustainable public health use. Zhu et al. [77] built their AIATBS (AI-Assisted Bethesda System), building on 81,727 historical LBC cases (retrospective), which were validated prospectively through 34,403 LBC patient outcomes at 11 multiple medical institutions. AIATBS demonstrated > 92% sensitivity and 82.14% specificity, and its ability to recreate the Bethesda categorization performance for expert cytopathologists positioned it as a suitable diagnostic utility for adoption into scalable screening pipelines [78].

Artificial intelligence has potential in low-income contexts too but that will be discussed in more detail. The VIA-AI system showed promise to reducing overtreatment and providing screening access in a more limited health care environment. These large educational prospective studies demonstrate that AI-enabled cytology and visual screening systems could improve diagnostic performance, operational efficiency, and cost-effectiveness in real-world public health programs.

3.4. Strengths, Challenges, and Limitations

Global and relevant performance, especially in low- and middle-income countries, requires large multicenter datasets and rigorous externally validated performance evaluation [79]. Even more important, the opacity of decision-making processes in deep-learned systems continues to confuse clinicians and is a significant factor in implementing accountable AI approaches in cervical cancer systems [80]. Additional regulatory, ethical, and transparency issues are also a factor [81]. Another time-sensitive issue is algorithmic bias related to demographic and socioeconomic groups that are poorly represented in model development, which may lead to over- or underestimation of risk or inequitable clinical outcomes. Finally, AI systems are susceptible to data drift, which happens when the clinical practice and characteristics of the population shift and begin to deteriorate performance [82]. An AI system trained only on homogeneous groups will inevitably result in poor predictions or clinical recommendations for the unmonitored and variable population, which will ultimately contribute to existing health disparities [83]. Equity in AI-based decision-making relies on modelling diverse, demographically balanced training datasets, routine audits for discriminatory behavior, and bias-mitigation strategies during the model life cycle (Table 4) [84].

Table 4: Ethical Challenges in AI-Driven Cervical Cancer Care and Mitigation Strategies.

Ethical Risk	Description	Potential Impact	Mitigation Strategies	References
Patient Privacy & Data Security	To handle extremely sensitive clinical and genetic data, strong cyber security and governance systems are needed.	Data breaches, legal liability, erosion of patient trust.	HIPAA/GDPR compliance, encryption, federated learning, secure data infrastructure, role-based access control.	[85]
Algorithmic Bias	AI model performance may differ across demographic groups if training data lacks diversity.	Unequal diagnostic accuracy, treatment disparities, widened health inequity.	Balanced datasets, bias audits, fairness constraints, demographic-aware model calibration.	[86]
Lack of Explainability	Deep learning models often operate as "black-box" systems, limiting interpretability.	Reduced clinician acceptance, unclear clinical rationale, safety concerns.	Explainable AI (XAI), SHAP/LIME, transparent modeling frameworks, augmented clinician review.	[87]
Model Drift & Reliability	Model accuracy may deteriorate over time as real-world clinical data evolves.	Performance decline, increased clinical risk, incorrect recommendations.	Continuous monitoring, adaptive retraining, drift detection pipelines, periodic recalibration.	[88]
Informed Consent & Data Ownership	Ambiguity around how patient data is utilized in AI training and deployment.	Ethical and legal violations, patient distrust.	Transparent consent workflows, patient-centric data governance, opt-in consent models.	[89]
Over-Reliance on AI	Excessive dependence on automated decision tools without adequate clinical judgment.	Potential misdiagnosis and compromised care quality.	Human-in-loop systems, clinician education, safety guardrails, decision-support roles only.	[90]
Regulatory & Compliance Gaps	AI medical governance and certification pathways remain heterogeneous.	Inconsistent quality control, increased liability risk.	FDA/CE-aligned validation, third-party audits, ethical compliance frameworks.	[91]
Equity & Accessibility	Uneven AI deployment across resource-limited	Magnified healthcare disparity,	Low-cost AI, multilingual systems, edge computing, digital	[92]

	environments and populations.	inequitable outcomes.	health equity strategies.	
Psychological Risk & Misinformation	Patient-facing AI chatbots may disseminate incorrect medical advice or generate anxiety.	Delayed care, misinformation, psychological distress.	Evidence-validated NLP, safety filters, clinician escalation, regulated medical chatbot deployment.	[93]

4. Future look and Discussion

The introduction of web-based AI programs, including applications like CHAMP and remote survival-prediction tools [94], is an important step towards scalable and real-time clinical decision-support systems. In the upcoming time, some researchers should explore the AI techniques that work on making sure health systems, creating safer online AI systems, and also putting tested risk guesses into health systems [95]. AI-empowered technologies amplify access to screening by relocating analytical expertise to the most overlooked and low-resource settings, thus forming equity in access to management [96]. Automation will soothe the encumbrance of clinician tasks and downstream care expense, while AI algorithms have persistently illustrated higher fidelity in diagnostic accuracy and are more cost-effective than existing technology. The aforementioned developments collectively depict a prospective disruption to cervical cancer avoidance and governance, such that worldwide clinical results will improve while health inequities will be eliminated [97]. Associations must deliberately incorporate artificial intelligence technology into their universal cervical cancer eradication projects to accelerate progress toward the WHO targets. Acknowledging this prospect will require interoperability of medical records technology, as well as governmental oversight from the CE and FDA [98]. Governmental agencies will be competent to validate model accountability and independent oversight of personal practices [99]. Conclusively, all implementations must also be unbiased, meaning that the user interface for these tools must be multilingual and comprehensible, in order for AI-enabled screening and care pathways to protect the most vulnerable members of society. AI has the potential for providing an impressive and invasive tool for eradicating worldwide cervical cancer, even in the absence of established governance frameworks.

5. Conclusion

Tools that leverage artificial intelligence (AI) will soon change how we prevent and treat cervical cancer by expanding screening opportunities, accurately assessing a patient's risk of developing cervical cancer, and providing individualized clinical decision support to providers. In addition to utilizing technologies such as internet-based platforms to connect patients with providers, multimodal data integration, and automated workflows to improve access to services, reduce costs, and enhance diagnostic accuracy within the context of low-resource healthcare settings, the successful clinical translation of these tools will require comprehensive validation, data standardization, regulatory oversight from agencies such as the FDA and EC, as well as developing safe, interpretable, and unbiased systems. Additionally,

combining psychosocial monitoring with clinical care and encouraging cooperation between fields will be essential for fair, moral, and successful implementation.

Author Contributions

Conceptualization: Mohammad Mustufa Khan

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Writing: Aditya Prasad, Srishti Sharma

Review and Editing: Srishti Sharma, Mohammad Mustufa Khan

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (GO version) in order to improve language and grammatical correction. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data Availability

No new data were created or analyzed in this study.

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Conflicts of Interest

None.

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