ACHSM Asia-Pacific Journal of Health Management

REVIEW ARTICLE

AI-ENHANCED CERVICAL CANCER SCREENING: INTEGRATING AUTOMATED DIAGNOSTICS AND SELF-SAMPLING PLATFORMS

*Mehfooza. M[1, *], Haroon Basha.I[2], Divya Meena S[1], Utku Kose[3]*

1. School of Computer Science and Engineering, Vellore Institute of Technology University: Vellore, Tamil Nadu, India
2. AMET University, Chennai, TN, India
3. Dept. of Computer Engineering, Artificial Intelligence Application and Research Center, Süleyman Demirel University, Turkey

*Correspondence: mehfooza.m@vit.ac.in

ABSTRACT

This is a systematic review that summarizes the existing body of literature about the incorporation of artificial intelligence (AI) and automated diagnostic frameworks and scalable self-sampling systems to detect cervical cancer screening. The analysis particularly reviews AI use in risk stratification and image diagnostics applications and compares the performance metrics, scalability prospects, economic analysis, and practical implementation of the applications. The extensive review of peer-reviewed publications, by analyzing articles published during the 10-year interval between January 2014 and June 2024, shows that deep learning architecture consistently demonstrates sensitivity and specificity rates over 90%, which are much higher in controlled research studies than traditional cytology and colposcopy processes 1,37.

The integration of patient self-sampling approaches contributes greatly to the screening participation rates, especially when it comes to underserved and resource-restricted settings. Extensive implementation literature shows significant potential in terms of reducing costs and improving access to healthcare services, but major issues still exist when it comes to data heterogeneity, clinical validation processes, and integration frameworks in health systems. The aggregate results highlight the potential sponsorship these AI-based solutions have to achieve in enhancing the global cervical cancer prevention strategies and bring them closer to the potential goals of elimination set by the World Health Organization.

KEYWORDS

artificial intelligence, cervical cancer, automated diagnostics, sampling platforms

INTRODUCTION

THE GLOBAL BURDEN AND SCREENING EVOLUTION

Cervical cancer remains a severe women health issue at the global level, and especially high-income countries are compared to low- and middle-income countries (LMICs), in which 90% of the cervical cancer-related deaths are observed [23,33]. The ongoing burden of the disease is in the face of the existing measures to prevent the disease, which points to the necessity of new screening methods that can solve the current barriers in the implementation process. The screening techniques have been significantly advanced since the initial Papanicolaou smear cytology and visual inspection with acetic acid (VIA) to use molecular human papillomavirus (HPV) testing and new digital imaging techniques [13,38]. Recent developments stress the applications of artificial intelligence-based methods that promote the accuracy of the diagnosis and the effectiveness of the programs in terms of scalability. The importance of these technological advances to the health of the population is immense because the earlier the precancerous lesions are identified and managed, the fewer cases and deaths due to cervical cancer can be experienced [10,15].

CURRENT CHALLENGES IN SCREENING IMPLEMENTATION

In spite of the significant technological advancement, the issues of implementation have remained quite serious, especially in the environment with limited resources where the disease burden is the most severe [21,39]. The ongoing use of highly qualified staff to interpret cytologic images and perform colposcopic evaluation and a high degree of disparity in diagnostic accuracy and inadequate healthcare facilities pose significant obstacles to the realization of universal screening coverage [21,39]. Self-sampling of HPV test is one of the strategies that have been shown to contribute to better involvement of participants and lower the cost of the program, yet its combination with AI-based triage and diagnostic systems is not explored thoroughly [8,25]. Moreover, although AI algorithms have been shown to be highly accurate in terms of image recognition and lesion classification related tasks, there are multiple constraints that can hinder their implementation in everyday clinical settings. These are the lack of well annotated datasets, variability of the domain on imaging platforms, and the lack of clinical validation in diverse populations [20,1,28].

CONCEPTUAL FRAMEWORK AND REVIEW OBJECTIVES

This review is designed based on three interrelated conceptual pillars, namely, automated diagnostics, scalable self-sampling platforms, and AI approaches towards risk stratification and image recognition. Automated diagnostics include AI-powered systems, which analyze cervical images or cytology slides to identify precancerous alterations with a minimum of human involvement 38,37. Self-sampling systems can be scaled to allow women to practice self-sampling, which allows women to comfortably acquire vaginal samples on their own and contributes to wide-range screening and accessibility [10,7]. The integrative component can be considered the AI algorithms, which links these elements together through offering advanced risk stratification and diagnostic assistance, in effect, linking molecular HPV outcomes with image-based tests [33,1]. The main goal of this systematic review is to provide a critical assessment of the processes of development, validation, and implementation of automated diagnostics and scalable self-sample systems in cervical screening based on AI algorithms to conduct the triage and image recognition processes. This systematic review will be used to evaluate the evidence on the accuracy, feasibility, and clinical usefulness of these technological advances and to fill any knowledge gaps and existing discussions in the area. This review will help to develop a progress towards improved cervical cancer prevention strategies especially in LMICs where the burden of the disease is the highest and the healthcare resources are the most limited ones.

METHODOLOGY

LITERATURE SEARCH STRATEGY

A literature scoping review was carried out based on the methodological recommendations of scoping reviews [42,43]. The search was conducted using various electronic databases such as Pubmed, Scopus, Web of science, and a few engineering and computer science repositories (IEEE Xplore, ACM Digital Library, and repositories arXiv). They were added as special repositories to retain the notable amount of AI and engineering-oriented studies that are not necessarily covered in biomedical databases. The search strategy was formulated to find peer-reviewed articles and conference papers that have been published since January 1, 2014, and June 30, 2024. The search was carried out on July 1012, 2024. The overall research question that informed the review was the following: What is the existing evidence on automated diagnostics and scalable self-sampling platforms in cervical screening with the help of AI algorithms to triage and identify images? In order to have a complete coverage, the main question was developed into particular search strings with Boolean operators and other MeSH/Emtree terms. One search query used in PubMed was: Artificial Intelligence"[Mesh] OR Deep Learning"[Mesh] OR Machine Learning"[Mesh]) AND (Uterine Cervical Neoplasma/diagnosis"[Mesh] OR Uterine Cervical Neoplasma/prevention and control"[Mesh] OR Mass Screening"[Mesh]). Other databases were done using similar adapted strings. No language filters were used initially, but only studies in English language were finally incorporated.

SELECTION CRITERIA AND PROCESS

Explicit inclusion and exclusion criteria were used in the selection of the study. The inclusion criteria included: (1) articles investigating AI/ML applications in the screening of cervical cancer; (2) articles involving self-sampling procedures; (3) articles that reported diagnostic accuracy or implementation outcomes; (4) articles in peer-reviewed journals or conference proceedings; and (5) articles published in various healthcare settings including LMICs. We also added conference proceedings to help capture newly emerging technology but the preliminary nature of the proceedings is recognized as a weakness of the synthesis. These exclusion criteria were: (1) non-English publications; (2) lack of primary data in the study (e.g., editorials, commentaries but no new data); (3) research on screening but not on treatment; and (4) articles older than 2014. The first database queries provided 265 distinct records. Citation chaining (both backward and forward) found one more 115 potentially relevant records and made a total of 380 candidate papers to screen the titles/abstracts. Upon screening of the title/abstracts on the inclusion/exclusion criteria, 369 papers were included to access full-texts. After full-text screening concerning relevance and methodological clarity, 50 studies were listed as highly relevant in accordance with predetermined criteria (methodological rigor, sample size and direct relevance to AI integration with screening/self-sampling and contribution to key outcomes). These 50 high-relevance studies that are mostly primary diagnostic studies, implementation research, and systematic reviews, draw the data used in the narrative synthesis and presented in the tables (Tables 1-3). The bigger group of 369 enlightened the larger contextual interpretation.

QUALITY ASSESSMENT AND DATA EXTRACTION

The scoping nature of the review and the heterogeneity of the included study designs (diagnostic accuracy, implementation science, health economics) made it impossible to use a single risk-of-bias tool. Rather, the common framework of relevance and methodological appraisal was derived out of scoping review methodologies. The evaluation of each study in this framework was based on: 1) Methodological Quality (objectives are clear, study design is appropriate, sample size is justified), 2) Clinical/Technical Relevance (clear application of this study to AI in cervical screening), 3) Reporting Completeness (reported outcomes, limitations are clear), and 4) Innovation/Potential Impact. Studies, which received a high score on these areas, were classified as highly relevant. In the case of diagnostic accuracy studies, we admit the possibility of high risk of bias (e.g., spectrum bias, verification bias, overfitting) that is typical of AI research. We do not blindly believe reported metrics such as sensitivity being greater than 90% and therefore make the interpretation that these metrics reflect the performance when certain research conditions are met and do not necessarily mean that it can be used in the real world to provide a superiority to the currently used methods. The extraction of data was conducted according to a unified protocol, which included the following characteristics of the studies, AI tool, and methods of comparison, measurement outcomes (sensitivity, specificity, AU), implementation, and limitations.

RESULTS: DESCRIPTIVE ANALYSIS OF INCLUDED STUDIES

The analysis of the literature shows that the area of research on AI use in cervical cancer screening is rapidly developing (Table 1) . The studies that have been included cover a wide array of technologies, such as deep learning-based image recognition, automated cytology analysis solutions, as well as integrated solutions that incorporate self-sampling with AI-based diagnostics.

TABLE 1: COMPREHENSIVE SUMMARY OF KEY STUDIES ON AI-ASSISTED CERVICAL SCREENING

Study	Primary Focus	Sample Size/Setting	Key Findings	Performance Metrics
[33]	HPV genotyping + AVE	Multi-country resource-limited settings	High sensitivity/specificity with combined approach; effective triage strategy	Sensitivity: 94%; Specificity: 91%
[1]	DL model validation	Multi-institutional dataset	Robust, reproducible deep learning model with strong clinical translatability	AUC: 0.89
[15]	Large-scale AI screening	Rural/urban China population	Successful full-coverage program with high efficiency and cost-effectiveness	Cost: ~US$7 per person
[10]	Self-sampling impact	Diverse healthcare settings	Participation increased 1.5-2.5 times; cost reduction of 32-48%	Acceptance: >85%
[38]	Automated dual stain	Multi-center validation	Improved specificity; reduced unnecessary colposcopies; cloud-based accessibility	Specificity: 93%
[37]	AI cytology grading	Large diverse datasets	Significant improvement in cytopathologist performance; enhanced diagnostic efficiency	Sensitivity: +13.3% improvement
[28]	AI + HPV in Zambia	High HIV prevalence setting	Effective risk-based triage; potential for point-of-care use in LMICs	AUC: 0.87
[39]	AI-supported screening	Urban/rural China	Low-cost implementation; high participation rates; integrated health worker model	Cost: ~US$6.31 per woman

GEOGRAPHICAL AND METHODOLOGICAL DISTRIBUTION

The articles considered are a research work conducted on a global scale, and some of the major contributors of the research are China, the United States, other European states and various LMICs such as Zambia, Uganda and Indonesia. This geographical diversity offers a good avenue of understanding how AI technologies are used in various health care systems and resource settings. The studies have a variety of designs, such as laboratory-based development of the algorithm, clinical validation studies, randomized controlled trials, implementation research, and systematic reviews, methodologically. Most studies that dealt with AI concentrated on convolutional neural networks (CNNs) and deep learning models, whereas self-sampling studies have focused on usability, acceptability, and agreement with clinician-collected samples.

THEMATIC ANALYSIS: AI ALGORITHMS FOR TRIAGE AND DIAGNOSIS

Technical Architectures and Performance:

The reviewed literature demonstrates substantial advancement in AI algorithms for cervical image analysis and triage decision support (Table 2) [1,31]. Deep learning models, particularly convolutional neural networks (CNNs), have emerged as the predominant architectural approach, achieving consistently high performance metrics across multiple studies [1,31]. These models have demonstrated remarkable capability in identifying subtle morphological features associated with precancerous changes, including nuclear enlargement, hyperchromasia, and nuclear membrane irregularities. Recent innovations include the development of transformer-based architectures and multi-branch deep learning models that capture both local and global image features, further enhancing diagnostic accuracy [3,36]. Several studies have incorporated attention mechanisms that improve model interpretability by highlighting regions of interest corresponding to clinically relevant features [20].

Integration with Molecular Diagnostics

One of the major tendencies of recent studies is the combination of AI-based image analysis with molecular tests, in particular HPV genotyping. Such multimodal strategy has proven to be better performing than the two methods alone resulting in better ability to stratify risks and triage decisions [33,28]. HPV16/18 genotyping coupled with automated visual evaluation (AVE) has demonstrated specific potential in locating women with the greatest risk of progressive disease and reducing the number of women referred to colposcopy needlessly. The improved methods use other molecular biomarkers including p16/Ki-67 dual staining and the use of methylation markers and then develop a total risk assessment algorithm to inform clinical decisions 38,32. Such integrated systems are a step towards customized screening guidelines in accordance with individual risk factors as opposed to blanket ones.

Performance Validation Across Modalities

AI algorithms have been tested on various imaging modalities such as colposcopic images, liquid-based cytology images, whole slide images and on visual inspection with acetic acid (VIA) images. Results indicate consistent values of AUC of above 0.85 and most models demonstrate performance measures of above 0.90 30,37. Liquid based cytology analysis generally has the highest performance whereas VIA-based applications exhibit more fluctuating outcomes owing to discrepancies in image quality and acquisition procedures 11.

TABLE 2: PERFORMANCE COMPARISON ACROSS AI APPLICATIONS

Application Area	Typical Sensitivity	Typical Specificity	Primary Challenges
Liquid-based cytology	92-97%	89-94%	Dataset diversity; annotation consistency
Colposcopic image analysis	88-93%	85-91%	Image quality variability; lighting conditions
VIA image interpretation	80-90%	85-95%	Standardization; subjective reference standards
Whole slide imaging	93-98%	90-96%	Computational requirements; storage needs

THEMATIC ANALYSIS: SELF-SAMPLING PLATFORMS AND INTEGRATION

Technological Developments and Acceptability

HPV testing on self-sampling has experienced a major technological development of a swab-based system to the more advanced and complex collection kits with built-in preservation medium. The literature reviewed presents a high level of acceptability among various groups of people and the preference rates of self-sampling instead of clinician collection are observed in the majority of the reviewed literature as between 60% and 85% [10,8]. The perceived privacy, convenience, comfort, and aversion towards pelvic examinations are the main factors that should be considered when determining acceptability. The latest innovations are aimed at creating easy-to-use equipment with easy-to-follow instructions, proper ergonomics, and inbuilt sample adequacy indicators. The support methods such as mobile apps and video tutorials have also enhanced appropriate sample collection and confidence among the users 2[5,41].

Integration with AI Diagnostics

Self-sampling combined with AI-controlled diagnostics is a promising solution towards scalable cervical screening in particular. Other studies established that self-collected samples can be equivalent to clinician-collected samples when subjected to current PCR-based tests and treated using AI algorithms [33,7]. The internet based platforms have proven to be a good means of delivering self-sampling kits, support in instruction and reporting of results. Such systems normally embrace the use of digital health technologies in registering participants, tracking the kits, delivering the results, and organizing the follow-ups [25,41]. Results interpretation and risk stratification may be performed automatically through the introduction of AI elements and, thus, the triage of HPV positive women will become efficient without involving clinicians instantly.

Impact on Screening Coverage and Participation

The greatest benefit of self-sampling methods is that they have been shown to boost screening attendance rates, especially those in hard to reach and underscreened groups. Research has continued to record higher participation rates of 1.5 to 2.5 times than the traditional screening invitations [10,8]. This has been more especially in the rural community, low-resource settings, and among women who have already refused clinic-based screening. Self-sampling allows overcoming numerous traditional impediments to screening participation, such as transport issues, time, cultural modesty, and prior unsuccessful experiences with healthcare [10]. Self-sampling platforms together with AI-based diagnostics will establish end-to-end diagnostics screening pathways that reduce the necessity of dedicated healthcare infrastructure but retain the high diagnostic quality of the procedures.

THEMATIC ANALYSIS: IMPLEMENTATION IN RESOURCE-LIMITED SETTINGS

Adapted Technologies for Low-Resource Environments

A substantial part of the examined literature is concerned with the adaptation of AI technologies to apply them in the resource-limited environment, especially in the LMIC where the epidemiological burden of cervical cancer is the largest. Some of these adaptations involve the creation of lightweight AI models, which can be used in mobile devices, the creation of portable imaging systems, and cloud-based systems that reduce the need to have a lot of local infrastructure 26,29. Applications that can be operated through Smartphone have become one of the most promising tools in low-resource environments, where mobile technology is diffused widely, and thus used to facilitate cervical screening. The latter applications usually include image acquisition scheme, AI-based analysis, and result reporting features within one unified system [11,14]. Various researches have found out that community health workers who are least trained can effectively use these tools to carry out the screening and make relevant decisions regarding referral.

Task-Shifting and Workforce Development

When AI-assisted screening is introduced in LMICs, the strategy that is regularly implemented is task-shifting which enables nurses, midwives, and community health workers to carry out screening services that were once undertaken by physicians. This method contributes to solving severe gaps in the number of specialized healthcare staff and at the same time ensures the quality of screening with AI-based decision support [28,21]. Healthcare worker training opportunities are usually oriented to the work with a device, its control of image acquisition and control over the quality of the results, as well as to the proper procedure of referral. Research has shown that given training and encouragement, non-expert medical personnel can reach screening accuracy similar to highly skilled practitioners under the guidance of AI-based applications [18,28].

Infrastructure and Logistics Considerations

The ability to implement successfully in any resource-restricted environment should be attentive to the facilities demand such as power supply, internet connectivity, systems of transportation of samples, and maintenance of technological equipment. A number of studies have come up with innovative solutions to these issues such as solar-powered charging system, offline mobile applications and hub and spokes modes of sample processing [39,15]. Cloud-based platforms have been especially useful in LMIC environments, which enables sophisticated AI analysis to be conducted remotely with only simple image acquisition requirements at the point of care. This would reduce the costs of high-cost local computing infrastructure and maintain access to the most developed AI algorithms [15,38].

CRITICAL ANALYSIS AND SYNTHESIS

Methodological Strengths and Limitations

The literature review shows that various methodological strengths have been used, such as, in most studies, the use of multi-centers datasets, prospective validation designs, and comparison with histopathological gold standards (Table 3). Nevertheless, there are still major limitations that influence the interpretation and extrapolability of results.

TABLE 3: CRITICAL ANALYSIS OF METHODOLOGICAL ASPECTS

Aspect	Strengths	Limitations
Study Design	Increasing number of prospective studies; multi-center collaborations	Limited long-term follow-up; few randomized controlled trials
Dataset Diversity	Efforts to include diverse populations; multi-ethnic representation in some studies	Still predominantly limited to specific regions; insufficient representation of some ethnic groups
Reference Standards	Use of histopathology gold standard in many studies; expert consensus panels	Verification bias in some studies; variability in reference standards
Technical Validation	Internal validation reported in most studies; some external validation efforts	Limited independent external validation; reproducibility testing insufficient
Clinical Integration	Some studies report real-world implementation experiences	Few studies assess integration into existing healthcare systems

Consistency and Variability in Findings

The literature reviewed shows that there is a general consistency when it comes to the accuracy of AI algorithms in diagnosis with the majority of studies reporting sensitivity and specificity of over 90% precancer detection. Nonetheless, there is great inconsistency in the performance measures of different works, which depend on different factors such as image acquisition scheme, image characteristics, AI structure, and image benchmarks. Research shows a constant increased screening attendance when self-sampling sampling methods are used but the degree of increased attendance is different depending on the population, invitation strategy and the cultural backgrounds. Likewise, although there is a lot of publicity on cost cuts, the magnitude of savings is limited to the scale of implementation, prevailing infrastructure and nature of healthcare systems.

Addressing Bias and Confounding Factors

The existing evidence base is subjected to several possible biases. The problem of verification bias is especially alarming in investigations whereby only those women who had positive screening test outcomes/lesion or could see them, receive confirmatory tests, which may exaggerate sensitivity estimates [14]. Spectrum bias is an issue that could be encountered in such studies that are based in specialized referral centers and not general screening populations. The high number of studies in high volume research centers might provide expertise bias that could overestimate performance that could be reached in the real practice. Also, the developers of technologies often fund the studies themselves, which also causes a possible conflict of interest that should be taken into account during the interpretation of the results.

IMPLEMENTATION CHALLENGES AND BARRIERS

TECHNOLOGICAL AND INFRASTRUCTURE BARRIERS

There are a number of technological obstacles to the use of AI-assisted cervical screening, especially in resource-constrained locations. These are unstable electricity, low internet access, poor technology maintenance facilities and lack of sufficient digital infrastructure [21,39]. The quality and performance of devices may have an impact even in cases where technology is used; differences in quality and performance may influence the quality of image form and further AI analysis. There are also other difficulties in remote locations with sample transportation and storage. Self-collected samples are frequently to be delivered to centralized laboratories to be processed and in such cases, an effective cold chain network and efficient logistics networks are necessary [10,41]. Transportation delays or cold chain interruptions may damage the quality of samples and influence the accuracy of the test.

WORKFORCE AND TRAINING REQUIREMENTS

Effective AI-assisted screening is impossible without the right workforce development and training programs. The healthcare personnel must be trained not only on the technical aspects of using the devices, as well as collecting samples, but also the interpretation of the results offered by AI and the correct decisions regarding the process of patient treatment [18,21]. Another important obstacle is resistance to technological change in the field of healthcare professionals. The clinicians might also be reluctant to embrace AI technologies because they fear loss of jobs, lacks trust or even aversion to technology-based healthcare reasons [17]. To overcome this resistance, it is necessary to show evident clinical benefits, conduct extensive training, and engage clinicians in the planning of the implementation.

REGULATORY AND QUALITY ASSURANCE CONSIDERATIONS

The regulation of AI-based medical devices remains dynamic, and it is unclear how to get approval and what compliance standards to follow. The regulatory standards of medical devices, software as a medical device (SaMD), and in vitro diagnostics vary across different countries, making it more difficult to implement AI screening solutions worldwide [17,19]. To guarantee the uniformity of the AI algorithms in various environments and populations, quality assurance programs should be designed. Such programs are supposed to involve periodic performance monitoring, updating of algorithms with new data, and controlling the performance decadence or drift with time [1,20].

ECONOMIC AND SUSTAINABILITY CHALLENGES

Although AI-assisted screening may be promising in terms of cost reduction, the initial cost of the technology purchase, infrastructure building and employee training may be high [39,15]. A majority of healthcare systems especially those in the LMICs have a constraint in their budget that restricts their capacity to invest in these upfront costs. The models of sustainable financing should be created to cover the current expenses of the AI-assisted screening programs, such as the software updates, equipment maintenance, consumables, and employee education. Even a successful implementation of the programs can become a problem without a sustainable financing to ensure long-term functioning of the program 15,6.

ETHICAL, LEGAL, AND SOCIAL IMPLICATIONS

Data Privacy and Security Concerns

There is a high concern on data privacy and security when using AI-assisted screening especially when this technology is used with cloud-based technologies and mobile applications. HIPAA and cervical images are sensitive personal information that must be well protected against unauthorized access or breach [17,19]. Data warehousing and data collection should also adhere to the data protection laws including the General Data Protection Regulation (GDPR) in Europe or the Health Insurance Portability and Accountability Act (HIPAA) in the United States. Nevertheless, a significant number of LMICs do not have a full-scale data protection legislation, which results in the existence of regulatory loopholes that need to be sealed with the help of ethical principles and organizational rules.

Algorithmic Bias and Health Equity

A possible algorithmic bias is a serious moral issue in screening with the help of AI. Unless training datasets are made diverse enough, AI algorithms might not behave similarly to various demographic groups, possibly worsening any existing disparities in health [1,17]. It is especially relevant to cervical cancer that is already disproportionately represented among the populations that are marginalized. Interventions to promote health equity should incorporate a deliberate consideration of how a wide range of populations are represented in training data, routine audits of the way algorithms perform across demographic groups, and specific approaches towards accessing underserved groups of people [33,10]. In the absence of such initiatives, AI technologies will contribute to or even even increase the existing health disparities.

Informed Consent and Health Literacy

The application of AI technologies places some new complexities on the informed consent process. The patients should know how their data will be processed, what AI should help them with their health, and what are the limitations of the AI technology [17]. This will necessitate a concise communication strategy that is culturally sensitive and health literate to different levels. When self-sampling is cited, it can be difficult to have a really informed consent in the situation when it is not connected with a direct contact with a healthcare professional. There is a need to come up with digital consent procedures that will be both inclusive and user-friendly where women are made aware of the consequences of participation 25,41.

Regulatory Frameworks and Liability

The fast pace of the progress of AI technologies has exceeded the creation of proper regulations and liability standards. The issue of accountability in cases of AI malfunctions, whether it should be the developers, healthcare providers, or the institutions, are quite open in nature [19]. Such regulatory uncertainty can lead to adoption and innovation impairment. Quite extensive regulatory frameworks need to be established that allow patient safety and innovation. These outlines are to discuss the methods of algorithm validation and continuous monitoring, transparency, and the distribution of liability [17,32].

FUTURE RESEARCH DIRECTIONS

ALGORITHM DEVELOPMENT AND VALIDATION

Various approaches should be focused on in the future work on more efficient and universal AI algorithms. Federated learning algorithms that facilitate the training of models at different institutions without direct data exchange can be used to generate more diverse and representative training images and overcome privacy issues [17,20]. Demystified AI approaches that give clear decision making procedures will be critical in establishment of clinical confidence and easy adoption [32,9]. The need to determine the actual generalizability and define possible performance differences in the subpopulations necessitate the urgency of prospective multi-center validation studies in different geographical and demographic populations [1,14]. Such studies ought to use standardized protocols and outcome measures in order to make cross-study comparisons meaningful.

IMPLEMENTATION SCIENCE RESEARCH

The research on the implementation science should be oriented on the best plans of incorporating AI technologies into the current healthcare systems, especially in resource constrained environments. This involves analyzing various service delivery models, training methods and financing mechanisms in order to find out the most effective in particular circumstances [21,39]. More longitudinal research is required to determine the viability of AI-assisted screening programs in the long term, their effect on health outcomes, cost-efficiency, and health systems efficiency [15,6]. Such studies must also look at the way programs develop and change with the challenges and the emerging circumstances.

HEALTH ECONOMIC EVALUATIONS

There should be extensive health economic appraisals to inform the decisions in resource allocation and policy formulations. These assessments must not only consider the direct costs, but also the extended economic effects of the cost, such as productivity losses and opportunity costs [15,39]. The financing models should be contrasted to find the sustainable solutions related to different contexts of the healthcare system. Budget impact analyses may assist healthcare systems to realize the monetary cost of implementing AI technologies, such as the amount of funds needed to invest in these technologies and the expense involved in running them on a regular basis [10,8]. This is to be done through analysis of the potential cost saving due to less advanced treatment of cancer and better productivity.

ETHICAL AND SOCIAL CONSIDERATIONS

Future studies must cover such important ethical and social issues as measures against algorithmic bias, fair access, and culturally sensitive implementation methods [17,10]. Community engagement studies might be used to make sure that AI technologies are created and introduced in a way, which does not go against the community values and preferences. Research on the psychological effect of AI-assisted screening on the patient and healthcare provider is required to comprehend and overcome any possible concerns [18,4]. This involves studies on formation of trust, preference of decision making and communication strategies.

POLICY AND PRACTICE IMPLICATIONS

GUIDELINE DEVELOPMENT AND STANDARDIZATION

The facts presented in favor of AI-guided cervical screening can be used to build the new clinical guideline, involving the use of these technologies in practice. These guidelines are expected to give explicit guidelines on how and where to be used, quality standards and considerations to be taken during implementation [33,38]. International cooperation may assist in making the guidelines more harmonized between countries with some flexibility in adapting certain requirements of the context. Standardization attempts must aim at creating standardized image acquisition protocols, data labeling protocols, validation of protocols and reporting of performance [1,20]. Such standards will simplify the comparison of technologies, enhance the reproducibility of technologies, and help the regulatory approval processes.

HEALTH SYSTEM INTEGRATION STRATEGIES

The effective implementation of AI technologies presupposes the need to plan and develop capacities within healthcare systems. These involve the evaluation of infrastructure requirements, training, development, creating referral channels, and developing monitoring and evaluation systems [39,6]. The process of integration must be progressive and repetitive, and learning and adjustment influenced by experience are possible. Task-shifting interventions could be very useful in overcoming the shortage of workforce by allowing nurses, midwives and community health workers to carry out screening interventions with the assistance of AI [28,21]. Proper training, supervisory and career development opportunities should be provided to accompany these strategies.

FINANCING AND SUSTAINABILITY MODELS

The AI-assisted screening should have sustainable financing models that should be created in line with the overall healthcare financing systems. This can involve participation in national health insurance programs, performance-based funding structures or government-business alliances [15,10]. It should be financed not only on the initial implementation but also on the costs incurred due to the continuous implementation like software updates, equipment and quality assurance. Economic rationales of investment in AI-aided screening must focus on more than direct healthcare savings, but on more general economic benefits such as productivity improvements and economic growth [39,8]. Such arguments are able to facilitate in gaining political support and allocation of resources.

CONCLUSION

Connection of artificial intelligence with automated diagnostics and self-sampling systems is a radical approach to the screening of cervical cancer that will overcome the limitations of the traditional methodology. The accuracy in diagnostic tests by AI algorithms and especially deep learning models have been shown to be at consistently high levels surpassing the traditional cytology and human visual inspection methods. These technologies, when used together with self-sampling procedures, result in an astounding enhancement of screening accessibility and participation, especially in underserved and resource-constrained communities. The feasibility and cost-effectiveness of AI-assisted screening programs have been proven by large-scale implementation studies, particularly in LMICs [6,15]. These programs are based on cloud-based solutions, mobile devices, and the use of task-shifting solutions to address infrastructure and staffing limitations and ensure the delivery of high-quality screening services. The outcome would be a more scalable, effective, and patient-centered cervical cancer prevention method that is in line with the global elimination objectives. Nevertheless, there are still great challenges, which need to be met in order to achieve the maximum of these technologies. They are a lack of external validation of AI algorithms, bias and health equity in AI algorithms, infrastructure needs in resource-constrained environments and regulatory changes. Further research and development is also needed to ensure that the systems can be sustained in the long term and fit the established healthcare systems. Further development will require further innovation in the development of the algorithms, extensive research in a variety of populations, careful consideration of the implementation science, and an ethical and social concern. A cervical screening with AI and a proper level of investment, cooperation, and care regarding equity can significantly decrease the global cervical cancer burden and bring the world closer to the desired outcome of eradication.

AUTHORSHIP

All authors have made substantial contributions to the conception, design, and execution of this systematic review. Each author has contributed to the analysis and interpretation of the data, drafting and revising the manuscript, and has approved the final version for submission. The order of authors reflects their relative contributions to the work.

ACKNOWLEDGEMENTS

This research received no specific grant from any funding agency. The authors thank the anonymous reviewers and colleagues who provided valuable feedback during the preparation of this manuscript.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

References

1. Ahmed SR, Befano B, Lemay A, et al. Reproducible and clinically translatable deep neural networks for cervical screening. Sci Rep. 2023;13(1):1-12. doi:10.1038/s41598-023-48721-1.
2. Attallah O. Cervical cancer diagnosis based on multi-domain features using deep learning enhanced by handcrafted descriptors. Appl Sci. 2023;13(3):1916. doi:10.3390/app13031916.
3. Baba T, Miah ASM, Shin J, Hasan MAM. Cervical cancer detection using multi-branch deep learning model. arXiv. Preprint posted online August 14, 2024. https://doi.org/10.48550/arxiv.2408.10498.
4. Baleydier I, Vassilakos P, Vinals R, et al. Study protocol for a two-site clinical trial to validate a smartphone-based artificial intelligence classifier identifying cervical precancer and cancer in HPV-positive women in Cameroon. PLoS One. 2022;17(1):e0260776. doi:10.1371/journal.pone.0260776.
5. Cantley R, Jing X, Smola B, Hao W, Harrington S, Pantanowitz L. Validation of AI-assisted ThinPrep® Pap test screening using the GeniusTM Digital Diagnostics System. J Pathol Inform. 2024;15:100391. doi:10.1016/j.jpi.2024.100391.
6. Cervical cancer screening aided by artificial intelligence, China. Bull World Health Organ. 2023;101(6):381-390. doi:10.2471/BLT.22.289061.
7. Chang T, Chou H, Chao A, et al. Evaluation of a novel vaginal cells self-sampling device for human papillomavirus testing in cervical cancer screening: A clinical trial assessing reliability and acceptability. Bioeng Transl Med. 2024;9(3):e10653. doi:10.1002/btm2.10653.
8. Colonetti T, Uggioni MLR, Santos ALMD, et al. Self-sampling for HPV testing in cervical cancer screening: A scoping review. Eur J Obstet Gynecol Reprod Biol. 2024;296:20-51. doi:10.1016/j.ejogrb.2024.02.032.
9. Feng B, Xu C, Li Z, Li J, Zhang C. Study on artificial intelligence recognition pre-processing algorithm for cervical cancer. EAI Endorsed Trans Perv Health Tech. 2024;10:1-9. doi:10.4108/eetpht.10.7724.

10. Gomes M, Provaggi E, Pembe A, Olaitan A, Gentry-Maharaj A. Improving accessibility of cervical cancer screening: A global perspective on self-sampling and digital innovation. Preprints. Preprint posted online December 2024. doi:10.20944/preprints202412.1888.v1.
11. Harsono AB, Susiamo H, Suardi D, et al. Cervical pre-cancerous lesion detection: Development of smartphone-based VIA application using artificial intelligence. BMC Res Notes. 2022;15(1):1-7. doi:10.1186/s13104-022-06250-6.
12. Hemajothi S, Ravi V, Girinandanaa G, Joycerobega PD, Moncia K. Transformative advances in cervical cancer diagnosis leveraging colposcopy imaging with VIT. In: 2024 IEEE 5th Radiance International Conference on Advanced Computing and Communication Systems (ICACCS). IEEE; 2024:1-6. doi:10.1109/raeeucci61380.2024.10547840.
13. Hou X, Shen G, Zhou L, Li Y, Wang T, Ma X. Artificial intelligence in cervical cancer screening and diagnosis. Front Oncol. 2022;12:1-13. doi:10.3389/fonc.2022.851367.
14. Hu L, Mwanahamuntu MH, Sahasrabuddhe VV, et al. Internal validation of automated visual evaluation (AVE) on smartphone images for cervical cancer screening in a prospective study in Zambia. Cancer Med. 2024;13(11):1-11. doi:10.1002/cam4.7355.
15. Ji L, Yao Y, Yu D, et al. Performance of a full-coverage cervical cancer screening program using on an artificial intelligence–and cloud-based diagnostic system: Observational study of an ultralarge population. J Med Internet Res. 2024;26:e51477. doi:10.2196/51477.
16. Kalbhor M, Patel H, Saldanha W, Shinde S, Rathod T, Satapure P. Improving cervical cancer detection through machine and deep learning algorithms. In: 2024 International Conference on Computing and Communication Systems (IC3S). IEEE; 2024:1-6. doi:10.1109/iccubea61740.2024.10775038.
17. Khare SK, Blanes-Vidal V, Booth BB, Petersen LK, Nadimi ES. A systematic review and research recommendations on artificial intelligence for automated cervical cancer detection. Wiley Interdiscip Rev Data Min Knowl Discov. 2024;14(4):1-25. doi:10.1002/widm.1550.
18. Kim S, An H, Cho HW, et al. Pivotal clinical study to evaluate the efficacy and safety of assistive artificial intelligence-based software for cervical cancer diagnosis. J Clin Med. 2023;12(12):4024. doi:10.3390/jcm12124024.
19. Ledwaba L, Saidu R, Malila B, Kuhn L, Mutsvangwa T. Automated analysis of digital medical images in cervical cancer screening: A systematic review. medRxiv. Preprint posted online September 29, 2024. doi:10.1101/2024.09.27.24314466.
20. Li H, Sun Y, Zhu C, et al. Large-scale cervical precancerous screening via AI-assisted cytology whole slide image analysis. arXiv. Preprint posted online July 25, 2024. https://doi.org/10.48550/arxiv.2407.19512.
21. Li J, Wu R, Qu X, et al. Effectiveness and feasibility of self-sampling for human papillomavirus testing for internet-based cervical cancer screening. Front Public Health. 2022;10:1-11. doi:10.3389/fpubh.2022.938272.
22. Liu X, Bai J, Li N, et al. AI-assisted cervical cytology precancerous screening for high-risk population in resource limited regions using compact microscope. Res Square. Preprint posted online May 7, 2024. doi:10.21203/rs.3.rs-4513507/v1.
23. Menezes L, Vazquez L, Mohan CK, Somboonwit C. Eliminating cervical cancer: A role for artificial intelligence. In: Barber D, ed. Advances in Experimental Medicine and Biology. Vol 1194. Springer; 2019:149-163. doi:10.1007/978-3-030-29022-1_13.
24. Mirugwe A, Ashaba C. Cervical cancer screening: Artificial intelligence algorithm for automatic diagnostic support. Res Square. Preprint posted online September 12, 2023. doi:10.21203/rs.3.rs-3230760/v1.
25. Nakisige C, Fouw MD, Kabukye JK, et al. Artificial intelligence and visual inspection in cervical cancer screening. Int J Gynecol Cancer. 2023;33(11):1-8. doi:10.1136/ijgc-2023-004397.
26. Nurmaini S, Rachmatullah MN, Sanif R, et al. Real time mobile AI-assisted cervicography interpretation system. Inform Med Unlocked. 2023;42:101360. doi:10.1016/j.imu.2023.101360.
27. Ouh YT, Kim TJ, Ju W, et al. Development and validation of artificial intelligence-based analysis software to support screening system of cervical intraepithelial neoplasia. Sci Rep. 2024;14(1):1-12. doi:10.1038/s41598-024-51880-4.
28. Parham GP, Egemen D, Befano B, et al. Validation in Zambia of a cervical screening strategy including HPV genotyping and artificial intelligence (AI)-based automated visual evaluation. Infect Agent Cancer. 2023;18(1):1-12. doi:10.1186/s13027-023-00536-5.
29. Patel R, Patel M, Patel Z, Patel D. Current status of machine learning and artificial intelligence in cervical cancer screening and diagnosis: A systematic review. Glob Acad J Med Sci. 2024;6(1):1-15. doi:10.36348/gajms.2024.v06i01.008.

30. Qin D, Yin X, Rong G, Zhou S, Wang M, Pei Z. Meta-analysis of artificial intelligence-assisted pathology for the detection of early cervical cancer. Int J Comput Intell Syst. 2023;16(1):1-15. doi:10.1007/s44196-023-00367-7.
31. Ramesh H, Serkal AA, Kanso H, Aljallaf N, Mounsef J. Cerviscan: Advancing cervical cancer detection through deep learning innovations. In: 2024 IEEE 37th International Symposium on Computer-Based Medical Systems (CBMS). IEEE; 2024:1-6. doi:10.1109/cbms61543.2024.00064.
32. Rodríguez M, Córdova C, Benjumeda I, Martin SS. Automated cervical cancer screening using single-cell segmentation and deep learning: Enhanced performance with liquid-based cytology. Computation. 2024;12(12):232. doi:10.3390/computation12120232.
33. Sanjosé SD, Perkins RB, Campos NG, et al. Design of the HPV-automated visual evaluation (PAVE) study: Validating a novel cervical screening strategy. eLife. 2023;12:1-25. doi:10.7554/eLife.91469.1.
34. Sarhangi HA, Beigifard D, Farmani E, Bolhasani H. Deep learning techniques for cervical cancer diagnosis based on pathology and colposcopy images. Inform Med Unlocked. 2024;46:101503. doi:10.1016/j.imu.2024.101503.
35. Shamsunder S, Mishra A, Kumar A, Kolte S. Automated assessment of digital images of uterine cervix captured using transvaginal device—a pilot study. Diagnostics. 2023;13(19):1-12. doi:10.3390/diagnostics13193085.
36. Singh J, Kaliyar RK, Kumari R, et al. Advancements in early detection of cervical cancer using machine learning and deep learning models for cervicography analysis. In: 2024 3rd International Conference on Innovations and Developments of Advanced Technologies (ICIDAT). IEEE; 2024:1-6. doi:10.1109/innocomp63224.2024.00049.
37. Wang J, Yu Y, Tan Y, et al. Artificial intelligence enables precision diagnosis of cervical cytology grades and cervical cancer. Nat Commun. 2024;15(1):1-13. doi:10.1038/s41467-024-48705-3.
38. Wentzensen N, Lahrmann B, Clarke MA, et al. Accuracy and efficiency of deep-learning-based automation of dual stain cytology in cervical cancer screening. J Natl Cancer Inst. 2021;113(1):72-79. doi:10.1093/jnci/djaa066.
39. Wu T, Lucas É, Zhao F, Basu P, Qiao Y. Artificial intelligence strengthens cervical cancer screening — present and future. Cancer Biol Med. 2024;21(6):1-16. doi:10.20892/j.issn.2095-3941.2024.0198.
40. Zeng X, Starr D, Li J, et al. AIcyte-alone capabilities as an independent screener for triaging cervical cytology using a 50% negative cutoff value. Cancer Cytopathol. 2024;132(8):1-10. doi:10.1002/cncy.22896.
41. Zhang Y, Du H, Wang C, Huang X, Qu X, Wu R. Feasibility and applicability of self-sampling based online cervical cancer screening: Findings from the China online cervical cancer screening trial. Infect Agent Cancer. 2024;19(1):1-10. doi:10.1186/s13027-024-00583-6.
42. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol. 2005;8(1):19-32. doi:10.1080/1364557032000119616.
43. Peters MDJ, Marnie C, Tricco AC, et al. Updated methodological guidance for the conduct of scoping reviews. JBI Evid Synth. 2020;18(10):2119-2126. doi:10.11124/JBIES-20-00167.