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Systematic Review

Diagnosis and Management of Sexually Transmitted Infections Using Artificial Intelligence Applications Among Key and General Populations in Sub-Saharan Africa: A Systematic Review and Meta-Analysis

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Abstract: The Fourth Industrial Revolution (4IR) has significantly impacted healthcare, including sexually transmitted infection (STI) management in Sub-Saharan Africa (SSA), particularly among key populations (KPs) with limited access to health services. This review investigates 4IR technologies, including artificial intelligence (AI) and machine learning (ML), that assist in diagnosing, treating, and managing STIs across SSA. By leveraging affordable and accessible solutions, 4IR tools support KPs who are disproportionately affected by STIs. Following systematic review guidelines using Covidence, this study examined 20 relevant studies conducted across 20 SSA countries, with Ethiopia, South Africa, and Zimbabwe emerging as the most researched nations. All the studies reviewed used secondary data and favored supervised ML models, with random forest and XGBoost frequently demonstrating high performance. These tools assist in tracking access to services, predicting risks of STI/HIV, and developing models for community HIV clusters. While AI has enhanced the accuracy of diagnostics and the efficiency of management, several challenges persist, including ethical concerns, issues with data quality, and a lack of expertise in implementation. There are few real-world applications or pilot projects in SSA. Notably, most of the studies primarily focus on the development, validation, or technical evaluation of the ML methods rather than their practical application or implementation. As a result, the actual impact of these approaches on the point of care remains unclear. This review highlights the effectiveness of various AI and ML methods in managing HIV and STIs through detection, diagnosis, treatment, and monitoring. The study strengthens knowledge on the practical application of 4IR technologies in diagnosing, treating, and managing STIs across SSA. Understanding this has potential to improve sexual health outcomes, address gaps in STI diagnosis, and surpass the limitations of traditional syndromic management approaches.

Keywords: Sub-Saharan Africa; sexually transmitted infections; HIV; key populations; general population; fourth industrial revolution; artificial intelligence technologies; algorithms

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1. Introduction

The Sub-Saharan Africa (SSA) region carries a disproportionately high burden of sexually transmitted infections (STIs), with a significant prevalence and incidence within individual countries. According to the World Health Organization (WHO), STIs, including HIV and viral hepatitis, account for approximately 2.3 million deaths annually, with more

than 1 million new infections occurring daily worldwide [1]. In SSA, the prevalence of STIs remains alarmingly high, particularly among key populations (KPs) such as sex workers, men who have sex with men, transgender people, incarcerated individuals, people who inject drugs, adolescent girls, and young women [2]. These groups are at an elevated risk due to specific high-risk behaviors and structural factors. The region faces significant public health challenges, with STIs like syphilis, chlamydia, and gonorrhea remaining more prevalent, despite increased screening efforts [3,4]. Untreated STIs can lead to severe health complications, including infertility, pelvic inflammatory disease, and an increased risk of HIV transmission [5].

Sexually transmitted infection diagnosis and management in SSA face numerous challenges, primarily due to the region's under-resourced healthcare systems. Current methods include laboratory testing, point-of-care testing, and syndromic management [6]. Syndromic management, which treats symptoms without laboratory confirmation, is commonly used in resource-limited settings but often leads to over- or under-treatment. Non-syndromic management, involving precise laboratory tests, offers more accurate diagnoses but requires infrastructure that is often lacking [7]. The Fourth Industrial Revolution (4IR) is characterized by the widespread adoption of advanced technologies, such as artificial intelligence (AI), machine learning (ML), deep learning (DL), and data analytics, which promise to improve the diagnosis and management of STIs [8–11]. These technologies enable more accurate diagnoses and personalized treatment plans, enhancing the quality of care [8,9]. However, their adoption is hindered by challenges, such as limited digital literacy, poor internet connectivity, and inadequate healthcare infrastructure [12,13].

These technologies can process large datasets quickly, enabling early detection and accurate diagnosis of STIs, particularly in KPs, which is critical for effective treatment and prevention efforts [14]. For instance, AI models have been successful in detecting and predicting STI outbreaks, managing treatment plans, and improving patient outcomes in developed countries [15,16]. However, in SSA, the adoption of these technologies faces significant challenges, including inadequate infrastructure, limited access to reliable data, and societal factors, such as stigma and cultural beliefs [17,18]. Despite these obstacles, there have been successful pilot projects in countries like Kenya, Egypt, and South Africa, where AI has been integrated into healthcare systems to some extent [19]. The potential for AI technologies to revolutionize STI management in SSA is clear, but widespread implementation requires overcoming significant barriers [13,20].

This study aims to address the gap in knowledge and implementation of AI technologies in the management of STIs among KPs and general populations in SSA. Despite the high burden of STIs and the potential of 4IR technologies to improve healthcare outcomes, the region has been slow to adopt these innovations [21]. By exploring how 4IR technologies can be harnessed to manage STIs more effectively, this study seeks to contribute to the broader goal of achieving Sustainable Development Goal 3 of the United Nations 2030 agenda, which aims to ensure healthy lives and promote well-being for all by 2030 [22,23]. The study will also assess the challenges and successes of early adopters of AI technologies in SSA, providing valuable insights that can inform future strategies for the region [24]. Ultimately, this research investigates how AI/ML applications can contribute to reducing disparities in STI care among key and general populations in SSA by advancing STI diagnosis and management. By promoting the use of advanced technologies, this study aims to improve health outcomes and contribute to the global fight against HIV and STIs [25,26].

2. Materials and Methods

2.1. Research Questions

This review sought to answer the primary question:

- What evidence exists regarding the effectiveness of AI technologies in the diagnosis and management of STIs among key and general populations in SSA, based on available studies and curated databases?

The secondary questions answered included:

- What AI technologies are currently documented in the literature for use in diagnosing and managing STIs among key and general populations in SSA, and what are their reported applications and limitations?
- What barriers and opportunities, including infrastructure, computational support, and database requirements, are identified in the implementation of AI technologies for STI diagnosis and management among key and general populations in SSA?

2.2. The Methods and Approach

This systematic review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and is registered on the International Prospective Register of Systematic Reviews (PROSPERO) (ID: CRD42023468734) [27]. (See Supplementary Material: SM S1 for the PRISMA checklist.) The study is guided by the WHO STI and HIV frameworks, informed by regional and national strategic plans and guidelines [28,29]. A systematic method was employed to identify, gather, and assess the grey literature and published primary studies ranging from journal articles, book chapters, and technical reports on the application of AI technologies in the diagnosis, treatment, and/or management of STIs and HIV among KPs and general populations in SSA. Eligibility and inclusion criteria were formulated to guide literature selection and minimize researcher bias [30].

2.3. Search Strategy and Database Searches

A consolidated search strategy was developed using relevant keywords, and medical subject heading (MeSH) terms related to STIs, AI technologies, KPs, and SSA were used. Electronic databases, including PubMed, Scopus, Web of Science, Science Direct, EBSCOhost, and Sabinet were searched for eligible studies published between the years 2015 and May 2024. In addition, manual random searches of online documents, grey literature, and technical reports on the websites of relevant organizations, including the World Health Organization (WHO), United Nations (UN), and Centers for Disease Control and Prevention (CDC) were also conducted. Online searches of full texts of primary studies conducted in SSA on the use or applications of AI and/or ML in the diagnosis, treatment, and/or management of STIs or STDs from 2015 were carried out.

Supplementary Material: SM S6 shows the search strategy employing Boolean operators AND, OR, and NOT to incorporate various combinations of keywords and phrases related to the research topic. Additionally, terms such as curable STIs and KP were included, along with a delineation of different types of KPs, such as sex workers, gay men, transgender people, people who inject drugs, and individuals in prisons. The study topic was broken down into short statements using original words, acronyms, and synonyms of the relevant words or terms. For example, (applications OR uses) AND (of 4IR OR ML OR AI OR AI AND ML) AND (diagnosis AND management) AND (STIs OR sexually transmitted infections) AND (key populations OR KPs) AND (Sub-Saharan Africa OR Angola OR Benin OR Botswana OR Burkina Faso OR Burundi OR . . ., OR Zimbabwe).

2.4. Eligibility Criteria

The inclusion and exclusion criteria were guided by the "population, intervention, comparison, and outcome" PICO framework (Table 1). Additionally, the constructs include context, period, language, and study design.

Table 1. Inclusion and exclusion criteria.

Component	Inclusion Criteria	Exclusion Criteria
P (population)	Studies involving adults—15 years and above for prospective primary studies and all age groups for retrospective studies; the general population in SSA and KPs at higher risk of STIs in SSA, such as men who have sex with men, transgender people, sex workers, people who inject drugs, people in prisons and detention/incarcerated people, adolescent girls, young women, and PLHIV; Sub-Saharan African countries, the region, and its subregions.	Studies involving children—14 years and below for primary prospective studies; general populations or KPs outside of SSA; countries outside of Sub-Saharan Africa.
I (intervention)	Studies examining the applications of AI technologies in diagnosing, treating, and managing STIs. Examples of AI technologies include ML, DL, Natural language processing (NLP), Neural networks (NN), linear regression, logistic regression, decision tree, Support vector machine (SVM) algorithm, naive Bayes algorithm, K-nearest neighbors (KNN) algorithm, K-means, random forest algorithm, dimensionality reduction algorithms, gradient boosting algorithm, AdaBoost algorithm, Graph Neural Networks (GNNs), Federated Learning, BERT, Explainable AI and others.	Other studies not examining the applications of AI technologies in the diagnosis, treatment, and management of STIs.
C (comparison)	Studies with or without a comparator group comparing different AI approaches; comparing AI approaches and traditional diagnostic methods and comparing AI approaches and standard of care.	
O (outcome)	Studies reporting outcomes related to diagnosing, treating, and managing STIs using AI technologies.	Studies reporting outcomes without using AI approaches.
S (Study Design/Characteristics)	Studies that use AI approaches in randomized controlled trials; cohort studies; prospective cohorts; retrospective studies; time series studies; case-control studies; descriptive, analytical, and quasi-experimental studies were conducted in English from 2015 onwards and available in full text.	Studies with unclear methodologies; lacking trustworthiness, reliability, and validity of the research designs; clear biases; conducted using non-English and before 2015; not available in full text (abstract only), incomplete articles, and unpublished materials.
Subject matter	Studies on the diagnosis, treatment, and management of STIs using AI technologies.	Studies not addressing the use or applications of AI in the diagnosis, treatment, and/or management of STIs.
Literature type	Primary studies—journal articles, book chapters, theses and dissertations, conference presentations, grey literature, and unpublished studies.	All secondary studies—reviews, meta-analyses, editorials, and opinion discussions.

2.5. Selection and Screening of Documents

Two independent researchers, C.S. (Claris Siyamayambo) and E.P. (Edith Phalane) identified, selected, and included relevant studies on the applications of AI technologies in the diagnosis and management of STIs among KPs and general populations in SSA. The first author, C.S., independently screened documents for inclusion by identifying published articles, which were saved in RefWorks, according to their respective online database sources covering a wide range of scientific literature. The folders were then exported from RefWorks to Zotero and subsequently imported into Covidence for systematic review management. In Covidence, the second author, E.P., and the third author, R.N.P. (Refilwe Nancy Phaswana-Mafuya), participated in the selection of eligible documents. The study selection process involved three steps: First, C.S. reviewed the titles of all the studies to exclude irrelevant articles. Next, E.P. and C.S. collaboratively reviewed the abstracts of the eligible studies to ensure relevance. Finally, full-text reviews were conducted independently by C.S. and E.P., with R.N.P. consulted to resolve any conflicts regarding the eligibility of documents. Decisions on inclusion were based on predefined eligibility criteria related to the research objectives.

Study characteristics included first authors, year of publication, location country/region, study population, sample size, subject matter/approach, gender of participants,

and age of participants. Secondary reviews, meta-analyses, incomplete articles, unpublished materials, and non-English records were excluded from the study. Furthermore, we excluded articles with unclear methodologies, lacking trustworthiness or reliability and validity of the research designs, and studies showing clear biases.

2.6. Assessment of Quality

The quality of the study was assessed by following the Critical Appraisal Skills Programme (CASP) checklist, which is an appraisal tool that was used to assess the quality of studies used in this review [31–33]. (See Supplementary Material: SM S2 for the CASP checklist.) In addition, the TRIPOD reporting guidelines were used to assess the transparent reporting of prediction models used in the studies under review [34]. (See Supplementary Material: SM S3 for the TRIPOD +AI checklist.)

2.7. Data Extraction

The data extraction included all information about STI diagnosis, treatment, or management using AI technologies including information about study design and methodology, participant demographics and baseline characteristics, and numbers of events or measures of effect (where applicable).

2.8. Risk of Bias Assessments

The risk of bias and quality of included studies were assessed using appropriate tools in Covidence, including the Cochrane risk of bias tool for randomized controlled trials, and the Newcastle-Ottawa Scale for observational studies [35]. (See Supplementary Material: SM S4 and S5 for the Cochrane and Newcastle-Ottawa Scale tools.) The researchers utilized the key features of Covidence, such as importing references, screening tools, customizable forms, automatic duplication, risk of bias assessment, quality assessment real-time updates, and exporting data [36]. These key features of Covidence helped the researchers to be efficient and rigorous, by guaranteeing transparency, reproducibility, and reliability in the synthesis of gathered evidence.

2.9. Search Results

Following the eligibility and inclusion criteria, 1426 references were imported into Covidence for title and abstract screening. Of these, 861 duplicates were removed, leaving 565 studies for further evaluation. Upon screening the title and abstract, 70 studies were excluded due to content not meeting the inclusion criteria. Subsequently, 495 studies were assessed for full-text eligibility, and 41 studies were not retrieved, as the full text was unavailable. This means 434 studies underwent full-text screening, where further evaluation was conducted based on eligibility criteria, inclusion and exclusion criteria, and methodological adequacy. However, most of the full texts did not meet these requirements and were consequently dropped. Twenty studies fully met the eligibility criteria, inclusion and exclusion criteria, and methodological adequacy; hence, they were reviewed for study outcomes. Figure 1 illustrates the PRISMA steps followed during the screening process to identify eligible publications.

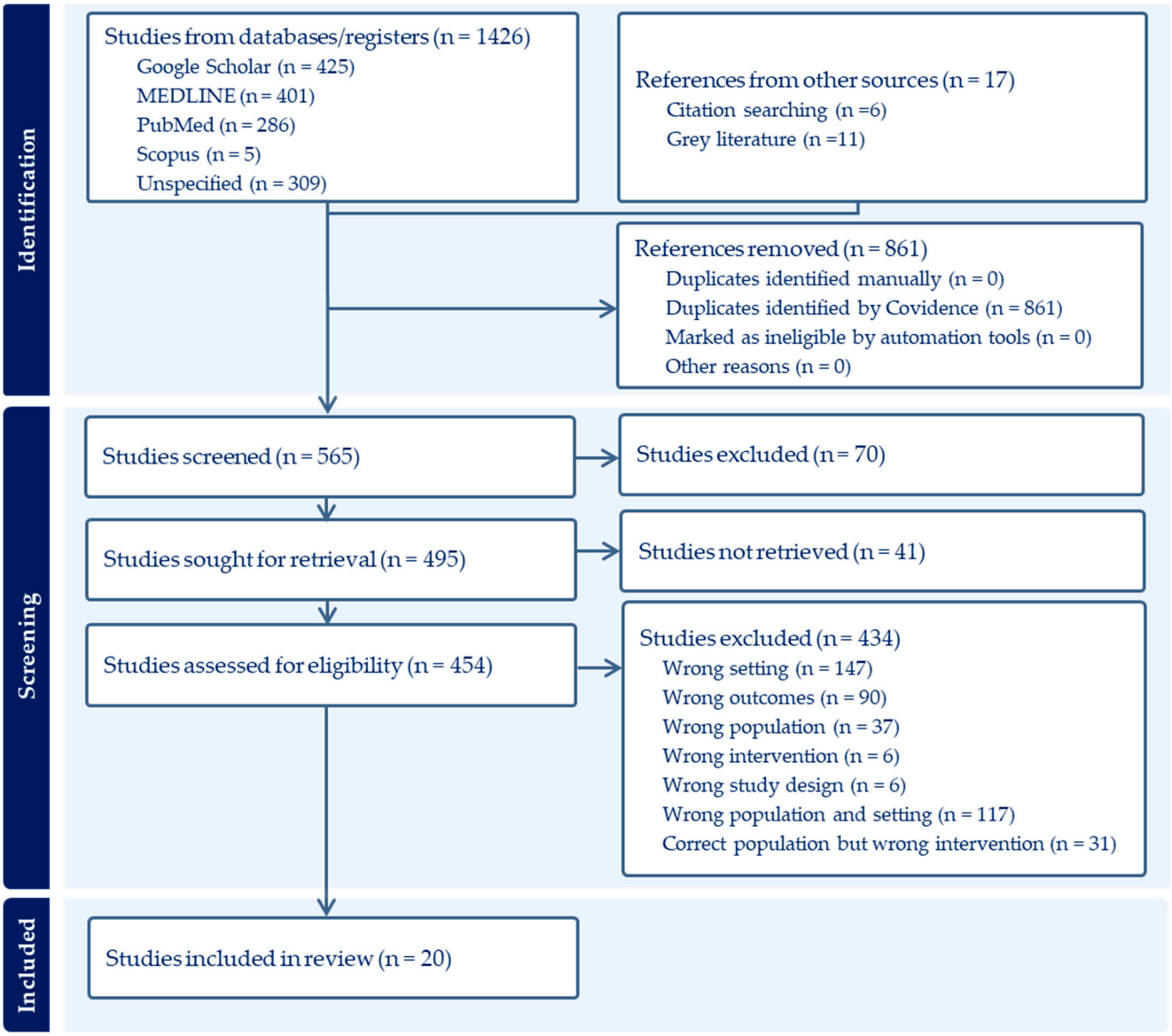


Figure 1. PRISMA diagram (source: [27]).

2.10. Quality and Bias Assessment

The included studies were evaluated using the CASP tool, the Cochrane risk of bias Tool, and the Newcastle-Ottawa Scale. The Critical Appraisal Skills Programme tool offers a checklist to assess the qualities of the studies reviewed. The risk of bias in the included studies was assessed systematically using the Cochrane Risk of Bias Tool, which examines bias across domains such as randomization, blinding, and selective reporting. The quality of the non-randomized studies reviewed was systematically assessed using the Newcastle-Ottawa Scale, which evaluates studies based on selection, comparability, and outcome domains. Most studies had clear aims, utilized appropriate methodologies addressing research questions relevant to ML algorithms, and presented results with well-supported conclusions. Ethical considerations were generally observed; although, some studies lacked detail. The CASP assessments rated most of the studies as high quality because of appropriate research designs that were relevant and rigorous, including the support of well-defined datasets. However, References [37,38] were rated as moderate quality studies because of unclear representativeness and generalizability concerns. Furthermore, since all the studies reviewed were not randomized trials, randomization, and allocation concealment were not

applicable using the Cochrane risk of bias tool. Most studies exhibited a moderate risk of bias because of the absence of blinding the outcome assessments, incomplete data handling, and selective reporting. Conflicts of interest were often addressed, though not universally stated. Generalizability was frequently limited, with biases introduced by the reliance on specific datasets or settings. The Newcastle-Ottawa Scale highlighted concerns about representativeness and comparability in some studies, though exposure ascertainment was consistently clear. Supplementary Material: SM S8 presents the full assessment, and the domains considered.

3. Results

3.1. Study Characteristics

Table 2 outlines the characteristics of the 20 studies included in this review on the application of AI technologies in STI diagnosis and management across SSA [37–56]. Only 20 of 49 SSA countries [57] reported on this subject, with Southern Africa being the most studied region, led by South Africa and Zimbabwe, followed by Malawi, Eswatini, Namibia, Lesotho, Mozambique, and Angola, totaling 11 studies. East Africa contributed 10 studies, with Ethiopia leading followed by Kenya, Tanzania, Rwanda, Uganda, and Burundi. In West Africa, Côte d'Ivoire had only two studies followed by Guinea, Liberia, Nigeria, and Sierra Leone together contributing to five studies, while Central Africa was represented by only one study from Cameroon. Notably, one study included countries across all four subregions [44], and two studies spanned East and Southern Africa [51,54].

Table 2. Characteristics and AI approaches of the studies on the diagnosis and management of sexually transmitted infections in Sub-Saharan Africa.

Author, Year, Region	Study Design	Population and Sample Size	AI Approaches	Implementation Classification and Comparator	Main Findings	Outcomes
Adeboye et al., 2023, West Africa [37]	Retrospective observational study.	Students, staff, and non-staff (males and females, aged 9–60 years, n = 400).	Logistic regression, KNN, decision tree, naive Bayes, random forest, and AdaBoost.	Methodological, no comparator specified.	Logistic regression was the best-performing model for diagnosing STIs, achieving ~95% accuracy.	Classification accuracy, AUC, recall, and F-score of the logistic regression model.
Alie and Negesse 2024, East Africa [39]	Retrospective study.	Adolescent respondents (n = 4502).	J48 decision tree, random forest, SVM, multi-layer perceptron, naïve Bayes, logistic gradient boosting, and logistic regression.	Methodological, no comparator specified.	J48 decision tree algorithm demonstrated high accuracy in detecting HIV positivity and predicting testing behaviors.	Knowledge of HIV testing probability and predictors based on awareness of AIDS and STIs.
Alzubaidi et al., 2023, East Africa [40]	Observational study.	Both genders aged ≥18 years (n = 854).	AI algorithms using computer vision technology.	Methodological, client self-interpretation, pharmacy provider interpretation, and expert panel interpretation.	AI vision technology reduced false negatives, identified positives correctly, and avoided missed infections.	Sensitivity, specificity, positive predictive value, negative predictive value, and detection of missed infections.
Balzer et al., 2020, East Africa [38]	Retrospective observational study.	Males and females aged ≥15 years (n = 75,558).	Logistic regression, penalized logistic regression, generalized additive models, stepwise logistic regression, and ML algorithms.	Methodological, risk group, and model-based approaches	ML models were most effective in identifying individuals at risk for HIV and improving prevention strategies.	Efficiency and sensitivity of different strategies in predicting 1-year risk of HIV seroconversion.
Belete and Huchaiah 2023, East Africa [41]	Retrospective observational study.	Age and gender not specified (n = 78,877).	Deep learning models.	Methodological, no comparator specified.	Developed an accurate prognostic tool for predicting HIV/AIDS test results.	Model accuracy in prognostic prediction for HIV/AIDS outcomes.

Table 2. *Cont.*

Author, Year, Region	Study Design	Population and Sample Size	AI Approaches	Implementation Classification and Comparator	Main Findings	Outcomes
Birri Makota and Musenge 2023, Southern Africa [42]	Retrospective cross-sectional study.	Males and females living with and without HIV (Aged 15–49 females, 15–54 males, n = 6672).	Supervised classification-based machine learning approach.	Methodological, no comparator specified.	Predicted HIV infection using classification-based ML models.	Predictive performance for HIV infection diagnosis.
Chikusi 2022, East Africa [43]	Retrospective observational study.	Males and females (n = 6346).	Random forest, XGBoost, and artificial neural networks.	Methodological, feature engineering: home-based community VCT, mobile testing, outreach testing, and VCT.	Identified HIV knowledge as the most significant element contributing to HIV index testing or assessment.	Mean absolute error (MAE) for random forest, XGBoost, and artificial neural networks.
Chingombe et al., 2022, Southern Africa [44]	Retrospective observational study.	Males and females (n = 20,577).	Random forest, SVM, and logistic regression.	Methodological, no comparator specified.	ML models identified high-risk individuals for targeted HIV prevention and screening strategies.	Targeted HIV prevention and screening strategies.
Chingombe et al., 2022, Southern Africa [45]	Retrospective observational study.	MSM (n = 1538).	DL and ML algorithms: RNN, bagging classifier, gradient boosting classifier, SVM, and Gaussian naïve Bayes classifier.	Methodological, traditional HIV testing approaches.	RNNs predicted HIV status with high precision, recall, and F1-scores, significantly improving early screening.	Precision, recall, accuracy, F1-score, and AUC for RNN and ML models.
Esra et al., 2023, Southern Africa [46]	Observational retrospective study.	ART patients (median age 33 years; n = 264,877).	Adaptive boosting, categorical boosting, logistic regression, and gradient boosting.	Methodological, no comparator specified.	ML model for patient retention on ART successfully validated and extended.	Interruptions in ART prediction, sensitivity, positive predictive value, and F1-scores.
Laybohr Kamara et al., 2022, West Africa [47]	Observational retrospective ecological study.	Males and females (aged 15–49 years; n = 158,408).	Geodetector and LASSO regression.	Methodological, no comparator specified.	LASSO model correctly predicted HIV prevalence, highlighting regional hotspots over time.	HIV prevalence patterns and spatial–temporal heterogeneity.
Mamo et al., 2023, East Africa [48]	Observational retrospective institution-based cross-sectional study.	HIV-positive adults receiving treatment (aged ≥18 years; n = 5264).	KNN, random forest, decision tree, gradient boosting, XGBoost, logistic regression, and SVM.	Methodological, no comparator specified.	Random forest classifier best predicted virological failure with high sensitivity and AUC.	Virological failure prediction based on viral load tests.
Maskew et al., 2022, Southern Africa [49]	Observational longitudinal study.	Males and females (median age 39 years; n = 809,977).	Logistic regression, random forest, and AdaBoost.	Methodological, no comparator specified.	ML models correctly identified HIV patients at risk for disengagement and unsuppressed viral load.	Patient retention and viral load suppression.
Mitiku 2023, East Africa [50]	Retrospective study.	Males and females (aged 20–39; n = 14,922).	Random forest, XGBoost, and artificial neural networks.	Methodological, manual HIV index case testing.	Random forest algorithm outperformed others in precision, recall, and F1-scores.	Development of HIV status predictive models for effective case testing.
Mutai et al., 2023, SSA Regions [51]	Observational study.	Males and females (n = 302,355).	Unsupervised machine learning.	Methodological, no comparator specified.	Identified clustered countries and predictors of HIV positivity using unsupervised ML.	Identification of HIV predictors and high-risk clusters.
Mutai et al., 2021, East and Southern Africa [52]	Observational study.	Males and females (n = 87,044).	Elastic net, KNN, random forest, SVM, XGBoost, and light gradient boosting.	Methodological, no comparator specified.	XGBoost significantly improved HIV positivity identification and screening for high-risk individuals.	Improved predictive accuracy for HIV positivity.
Oladokun et al., 2019, Southern Africa [53]	Retrospective cross-sectional study.	Women aged 15–49 years (n = 7808).	Decision tree and logistic regression.	Methodological, no comparator specified.	Decision tree showed higher sensitivity in HIV status classification than logistic regression.	Sensitivity, specificity, and overall predictive accuracy.

Table 2. *Cont.*

Author, Year, Region	Study Design	Population and Sample Size	AI Approaches	Implementation Classification and Comparator	Main Findings	Outcomes
Orel et al., 2020, SSA Regions [54]	Retrospective study.	Males and females (n = 124,777).	Penalized logistic regression, generalized additive model, SVM, and XGBoost.	Methodological, no comparator specified	XGBoost algorithm showed high accuracy in predicting HIV status.	Classification of HIV rapid diagnostic test images.
Turbé et al., 2021, Southern Africa [55]	Objective research design.	Image library (n = 11,374).	Deep learning algorithms: ResNet50, MobileNetV2, and MobileNetV3.	Methodological, traditional visual interpretation.	DL algorithms achieved 98.9% accuracy, outperforming traditional visual methods.	High accuracy in RDT image classification.
van Heerden et al., 2017, Southern Africa [56]	Infodemiology approach.	Males and females (Avg age 30.2 years, s.d. 2.3; n = 10).	HIV counseling and testing using conversational agents.	Methodological, human counseling, and testing.	Conversational agents were natural and equivalent to human counseling, fostering user openness.	Acceptability and feasibility of conversational agents for HIV counseling and testing.

HIV, human immunodeficiency virus; STI, sexually transmitted infections; RNN, recurrent neural networks, AI, artificial intelligence; ML, machine learning; DL, deep learning, IQR, interquartile range; MSM, men who have sex with men; s.d., standard deviation; HIVST, HIV self-testing; VCT, voluntary counseling and testing; AIDS, acquired immunodeficiency syndrome; SSA, Sub-Saharan Africa; CNNRNN, convolutional neural network–recurrent neural network; CNNLSTM, convolutional neural network–long short-term memory network; AUC, area under the curve; Api.AI, artificial intelligence application programming interface. N.B. The comparator refers to the reference or baseline method against which the AI technologies were evaluated in the studies.

A proportional distribution analysis of the countries studied in each subregion shows that Southern Africa has the highest representation, with 8 out of 10 countries (80%) using AI approaches, led by South Africa and Zimbabwe (five studies each). East Africa follows with 6 out of 15 countries (40%), with Ethiopia as the most studied, contributing five studies. West Africa's representation is 5 out of 15 countries (33%), with Côte d'Ivoire contributing two studies. Central Africa has the lowest proportion, with only one out of nine countries (11%), represented solely by Cameroon in one study.

The distribution of the studies varied from 2017 to 2024. There were a few studies per year from 2017, and the number increased towards 2024. Eight studies were published in 2023 looking at AI approaches used in the diagnosis and management of STIs in SSA. In addition, five studies were published in 2022, two in 2021, and two in 2020 including one study each in 2024, 2019, and 2017. There is an upward trend that becomes steeper as the years progress from 2017 onwards, as shown in Figure 2.

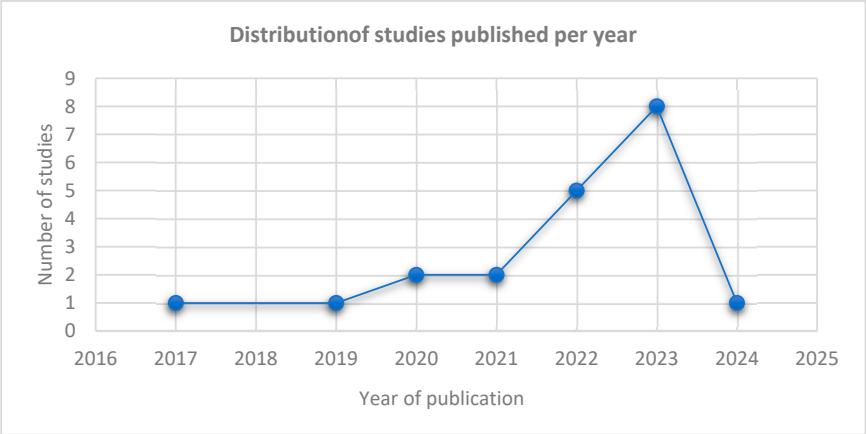


Figure 2. Studies on the diagnosis and management of STIs published in SSA from January 2017 to May 2024.

Furthermore, diversity in study designs was noted, ranging from retrospective observational studies (n = 16), objective research design (n = 1), infodemiology approach

(n = 1) that is focused on analyzing health-related information available in digital spaces like online searches, news media, blogs, and social media, institution-based cross-sectional studies (n = 1), and institution-based longitudinal studies (n = 1), where secondary data were used.

Most studies (n = 11) focused on STI prediction, with 10 specifically predicting HIV status. Only one study examined STIs broadly without focusing on HIV/AIDS [38]. Nineteen studies primarily targeted HIV, with one uniquely applying RNN and ML techniques to predict HIV status among MSM [48]. Other predictive studies addressed HIV prevalence [49], virological failure [42], treatment interruptions [45], and clinic attendance and viral load suppression [50]. Additional studies (n = 3) aimed to develop prognostic tools for HIV/AIDS using DL models [40], ML models for HIV index testing [43,46], and ML risk scores for HIV acquisition risk [53]. Two studies identified HIV predictors for screening [51] and clusters via unsupervised ML where the model is trained on unlabelled data without human supervision [44]. Image-based studies used AI algorithms including DL for interpreting HIV self-testing results (39) and classifying rapid HIV test images [52], and one study examined HIV counseling effectiveness using a conversational agent [56].

Participant demographics varied widely, including students, staff, and non-staff aged 9–60 years [38]; adolescents with unspecified ages [37]; males aged 15–54 and females aged 15–49 [41]; ART patients with a median age of 33 years (IQR 27–41) [45]; and HIV-positive adults aged ≥18 years [42]. Some studies included only women aged 15–49 [55] or unspecified image library samples [52]. Other studies sampled populations aged 15–49 [39], 15 years and above [53], and ≥18 years [47]. Reported ages included a median of 39 years (IQR 31–49) [50], an average age of 31.8 years for males and 32.1 for females [44], and 30.2 years (s.d. 2.3) for combined genders [56]. Some studies specified only the participant gender [46,51,54], while others focused on specific demographics, such as MSM without age details [48], or used narrow age bands [43]. Study sample sizes ranged broadly, from n = 10 to n = 809,977.

The study populations were derived from different data sources with most studies (10) using data from population-based assessments, demographic and health surveys (DHS), and community surveys; followed by data from health facility clinical records (4); HIV programmatic data and bio-behavioral data including rapid HIV test images (3), specifically population data (2) and data from purchasing sexual health products from pharmacies (1) as shown in Figure 3.

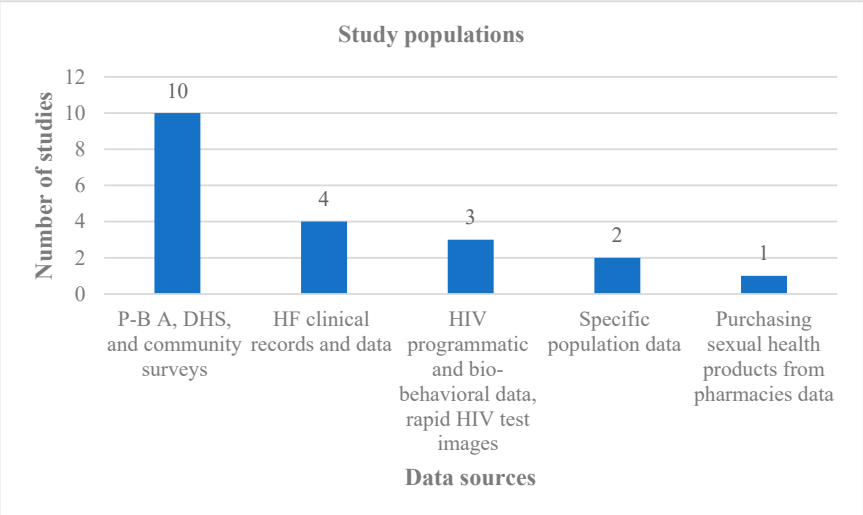


Figure 3. Study populations of reviewed studies.

The distribution of the reviewed studies, according to the subregions, countries, and years of publication, was analyzed. Eight countries from Southern Africa contributed to 11 studies published between 2017 and 2023 out of the reviewed 20, followed by six countries in East Africa contributing to 10 studies published between 2020 and 2024, five countries in West Africa contributing to three studies between 2022 and 2023, and Central Africa contributed to one study in 2023 (Figure 4).

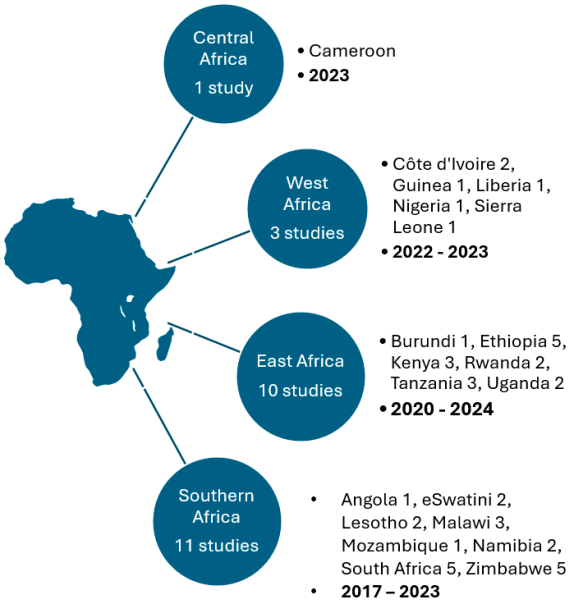


Figure 4. The distribution of studies according to Sub-Saharan African subregions and years of publication.

3.2. The Artificial Intelligence Approaches Used in the Diagnosis and Management of Sexually Transmitted Infections

Several AI approaches are used in the diagnosis and management of STIs in SSA. This study found that SSA primarily uses AI methods, including ML, for secondary data analysis. The focus is on extracting actionable insights from existing health records, surveys, and surveillance data to tackle significant healthcare challenges. Table 2 describes the AI and ML approaches used to diagnose and manage STIs using supervised ML, unsupervised ML, and DL algorithms [37,38,41,45,47,49,50,53–55].

Logistic regression and its advanced variations, including elastic net (which addresses multicollinearity) and stepwise logistic regression (used for feature selection), were effectively employed to diagnose STIs, predict HIV status, and assess infection risks. These methods enabled more accurate, data-driven public health interventions in SSA. These methods also helped predict treatment interruptions, clinic attendance, and viral load suppression [37,38,41,45,48,50,53,55,57]. In addition, the NNM included advanced architectures, like MLP, CNNs, RNNs, LSTM networks, and CNNLSTM hybrids. Multilayer perceptron (MLP), CNN, ResNet50, and LSTM were used for predicting HIV test status, developing prognostic tools for HIV/AIDS, and building predictive models for HIV index testing and status [40,43,46,48].

Furthermore, the tree models, including decision trees and XGBoost, addressed STI diagnosis, HIV testing, and virological failure prediction, and developed predictive models for HIV status and index testing [37,38,41–43,46,54,55]. Boosting algorithms, like AdaBoost and CatBoost algorithms, were used for diagnosing STI infection, predicting HIV status, clinic attendance, and interruptions in treatment. LightGBM also aided in predicting HIV infection and identifying high-risk individuals [38,41,45,50,51]. Moreover, random forest was applied for STI diagnosis, in particular HIV status prediction, and treatment outcomes,

such as virological failure and viral load suppression, while KNN assisted in HIV testing prediction and identifying high-risk individuals [37,38,46,48,50,51].

Naive Bayes and SVM were used to predict STIs and HIV test results, aiding decision-making for targeted prevention and screening strategies, while SVM helped predict virological failure [37,38,42,48,51]. Specialized techniques, like the Geodetector—a statistical tool used for spatial analysis to detect and quantify the relationships between geographical factors and a dependent variable predicted HIV prevalence, computer vision analyzed HIV self-testing images, and elastic net predicted HIV status. DL algorithms are useful in classifying rapid HIV test images, and a conversational agent API supported HIV counseling and testing [39,44,49,52,56].

The performance of these models was evaluated based on predictive values, the detection of missed infections, false-positive rates, and sensitivity. Key outcomes included identifying top models, predicting high-risk individuals, and supporting targeted HIV prevention and policy development [39,44,46,47,52,53]. The models also identified top-performing algorithms across different use cases, aiding in selecting optimal strategies for HIV/STI management.

Classification of Artificial Intelligence Approaches Based on Implementation: Practical Use Versus Methodological

All 20 reviewed studies were categorized as methodological, focusing on designing, developing, or testing AI methods in simulations or theoretical settings. None of the studies were conducted in real-world clinical settings or tested in practical implementations.

3.3. Study Comparators

Twelve of the studies did not use comparators, but different AI/ML algorithms or models used in the studies were compared against each other [37,38,40,42,44,45,47,49–51,54,55] (Table 2). However, in other studies, no comparator was specified; instead, the performance of algorithms was compared across different cohorts and countries [45,49]. In addition, one study compared AI approaches with client self-interpretation, pharmacy provider interpretation, and expert panel interpretation (consisting of three HIV self-test (HIVST) readers) [39]. On the other hand, the AI approaches were compared with the risk group and model-based approaches, using standard methods for constructing clinical prediction rules [53]. Traditional statistical approaches, traditional HIV testing approaches, and traditional visual interpretation by experienced nurses and newly trained community health worker staff were also adopted as comparators to AI approaches [41,47,52]. In the same way, human counseling and testing were compared to the AI approaches [56]. Additionally, home-based community voluntary counseling and testing (VCT), mobile testing, outreach testing, and voluntary HIV counseling and testing (VCT) were also used in another study compared with the AI approaches [46]. The manual nature of the current HIV index case testing was also a comparator against the AI approaches [43].

3.4. Successes, Opportunities, and Challenges Related to AI Approaches in STI Diagnosis and Management

Table 2 summarizes findings across various studies on ML and AI algorithms using STI diagnostics and management. Logistic regression emerged as the best algorithm for STI diagnosis based on correctly detecting symptoms (38), while the J48 decision tree performed optimally in detecting HIV positivity [37]. The XGBoost proved highly effective in predicting HIV status and identifying HIV predictors [41,51,54,55]. In addition, RNNs were identified as top classifiers for HIV prediction (48) and categorical boosting was superior in predicting patient retention on antiretroviral therapy [45].

Random forest models and algorithms excelled in predicting both virological failure (CD4 count as a key predictor) and clinic visit adherence [42,50]. They were also effective in viral load suppression prediction [50] and index testing for HIV, with HIV knowledge being a crucial factor [46]. On the other hand, AI computer vision algorithms showed perfect sensitivity and predictive value in interpreting HIV self-test images [39]. Further, unsupervised ML approaches identified male and female clusters relevant to HIV risk [44], and DL approaches effectively classified rapid HIV test images, reducing false positives and negatives [52]. Lastly, conversational AI agents were seen as user-friendly for HIV testing [56].

These AI technologies offer significant public health advantages, including enhancing screening, diagnosis accuracy, healthcare access, and strategic resource allocation [49,52,56]. However, for applications in SSA, factors like local settings, data sources, and technology quality require careful consideration [40]. The validation of these models may be necessary across diverse data and settings [38,42], with some models potentially benefiting from further optimization [45,50]. Additionally, performance assessment across different contexts and understanding factors influencing model success could enhance future predictive accuracy [43,46,48,53].

Most reviewed studies employed multiple AI approaches, except for three that used only one. The best-performing approach in each study, based on outcome metrics, was recorded as the top performer. In STI diagnosis, the random forest and XGBoost algorithms performed the best, excelling in five key metrics. Logistic regression and other unspecified ML algorithms ranked highest in each of the two metrics. Additionally, AI agents, algorithms, DL models, J48 decision trees, the LASSO model, and unsupervised ML approaches each achieved one top result.

3.5. Best-Performing AI Approaches

Most studies presented their main findings by evaluating the performance of various AI/ML approaches and identifying the best-performing methods. This review consolidates these outcomes by focusing on the top-performing AI approaches. As shown in Table 3, random forest emerged as the most successful algorithm, achieving the highest metric values in five instances. Similarly, XGBoost also achieved the five best performances. Logistic regression and other ML algorithms each demonstrated two top performances. Additionally, individual successes were observed for AI agents, other unspecified AI algorithms, DL models, J48 decision trees, LASSO models, and unsupervised ML approaches, with each achieving one best performance.

The AI/ML approaches can be categorized based on their primary uses. Prediction tasks were best addressed by random forest, XGBoost, logistic regression, DL models, and other ML models. For classification, the J48 decision tree, LASSO model, and other unspecified AI algorithms demonstrated strong performance. Clustering tasks were effectively handled by unsupervised ML approaches, while user engagement and counseling were best supported by AI agents. Additionally, visualization tasks were notably achieved using random forest and XGBoost. This categorization underscores the versatility of AI/ML approaches in addressing diverse aspects of HIV and STI research.

Table 3. Best performing artificial intelligence approaches.

AI Approach	Use of AI Approaches and Metrics
1. Random forest	(a) Predicting virological failure—sensitivity: 1.00, precision: 0.987, F1-score: 0.993, AUC: 0.9989 (b) Predicting clinic visits and viral load suppression: (i) Clinic visits—accuracy: 66–79%, sensitivity: 60.6%, specificity: 67%, negative predictive value: 94%. (ii) Viral load suppression—accuracy: 76%, sensitivity: 65.6%, negative predictive value: 95%. (c) Accuracy of ML algorithms—accuracy: 85%. (d) Predicting and visualizing HIV index testing—no specific metrics provided.
2. XGBoost	(a) Predicting likelihood of HIV infection—F1-score: 91.4% for males, 90.1% for females. (b) Enhancing HIV positivity identification—F1-score: 90% for males, 92% for females. (c) Predicting HIV status—mean F1-score: 76.8% for males, 78.8% for females. (d) Accuracy of ML algorithms—accuracy: 83.89%. (e) Predicting and visualizing HIV index testing—no metrics provided.
3. Logistic regression	Diagnosis and prediction of STD infection accuracy—classification accuracy: 95%, AUC: 94.6%, recall: 93.9%, F-score: 91.1%. Predicting HIV status—accuracy of 85%, recall of 98%, and F1-score of 92%.
4. ML models	HIV acquisition risk identification, predicting interruptions in treatment—no metrics specified.
5. AI agent	HIV counseling and testing—user acceptance: more than 60% found it natural, 70% felt comfortable, 60% guided to complete the test,
6. AI algorithm	HIV testing—sensitivity: 100%, negative predictive value: 100%, specificity: 99%, positive predictive value: 81.5%.
7. DL models	HIV status prediction: (a) RNN accuracy: 87%, precision: 87%, recall: 87%, F1-score: 87%, AUC: 94%. (b) ANN accuracy: 85.5%, precision: 84.4%, recall: 85.7%, F1-score: 85.1%, AUC: 89.72%.
8. J48 decision tree	HIV detection: accuracy: 81.29%, ROC curve: 86.3%.
9. LASSO model	Identifying HIV testing uptake factors—no metrics specified.
10. Unsupervised ML approaches	Identifying male and female HIV clusters—no metrics specified.

3.6. Reported Challenges, Evaluations, and Future Directions for AI Technologies in Healthcare

3.6.1. Limitations Cited by the Reviewed Studies

The reviewed studies revealed several significant limitations that need to be addressed. One major issue was data inadequacies, including the lack of consideration or absence of key characteristics, such as missing sociodemographic attributes, behavioral characteristics, and the omission of certain health issues. These gaps in data undermine the robustness and applicability of the findings. Additionally, procedural limitations were common, such as the use of small sample sizes, a focus on very few algorithms, insufficient assessment of model performance, and a limited scope of study objectives. Furthermore, limitations in study designs restricted the generalizability of the findings. A critical shortcoming across all studies was the predominant reliance on secondary data, without integrating AI approaches into primary healthcare settings, which limits the practical relevance of these studies to real-world applications.

3.6.2. Evaluation of Artificial Intelligence Approaches by the Reviewed Studies

The reviewed studies highlighted the widespread use of AI and ML approaches for data analysis. These methods consistently outperformed traditional, non-AI approaches, demonstrating high levels of precision, accuracy, and sensitivity. However, further validation of these outcomes with diverse datasets and settings is essential to confirm their superiority and relevance. Future research should also focus on identifying other factors contributing to the success of these models and determining the optimal conditions under which one model may outperform another. Additionally, it is critical to calculate comprehensive performance metrics and optimize models for more effective predictions. A deeper understanding of how AI approaches can be integrated into primary healthcare, especially in SSA, is vital. This includes considering the settings, data sources, and the quality of tech-

nical resources available. Validation of these approaches in real-world primary healthcare settings remains a key area for further investigation.

3.6.3. Summary of Future Research Directions by the Reviewed Studies

There are numerous avenues for future research regarding the application of AI technologies in real-life healthcare settings for diagnosing and managing STIs, particularly HIV. Many studies emphasize the need to validate the effectiveness of AI and ML approaches in STI diagnosis and treatment, while also addressing ethical considerations surrounding their integration into real-world healthcare. Further research is needed to explore the relevance and adaptability of AI and ML technologies in different healthcare settings and communities. Addressing data-related issues is also critical, as the reviewed studies often relied on inadequate datasets. Comprehensive datasets that capture relevant characteristics are essential to improve decision-making and inform effective health policies.

3.7. Meta-Analysis

Quantitative data were systematically extracted from the results sections of the reviewed studies using a structured extraction tool (see Supplementary Material: SM S7) to minimize bias and ensure consistency. The extracted data were entered into Microsoft Excel and then imported into R version 4.4.1 (2024-06-14 curt) for data cleaning and analysis. Extracted data included age-related statistics (mean, median, interquartile range, and standard deviation), sample sizes (including gender-based breakdowns), metric measures used to evaluate AI/ML approaches, and the countries and subregions of SSA where studies were conducted. Data cleaning involved checking for inconsistencies and missing values and ensuring accuracy and completeness. Descriptive analysis, including summary statistics and frequency analysis, was performed to prepare the data for meta-analysis. Studies with incomplete data, missing metrics, or insufficient study characteristics were excluded. Variables selected for meta-analysis were informed by their availability, relevance, and potential to address study objectives, resulting in the selection of five variables: study, sample size, use, AI/ML approach, and F1-score (used as the effect size). Only five studies reported age-related statistics, revealing a significant demographic data gap crucial for understanding population-level risks. Furthermore, some studies presented unique metrics or descriptive outcomes that, while valuable, were omitted from the meta-analysis because they were either qualitative or non-standardized. For the evaluation of AI/ML approaches, the F1-score was selected, as it was reported in nine studies, sometimes disaggregated by gender or across different methods, thereby providing more records. Also, the F1-score was selected because of its characteristic of representing the harmonic mean of precision and recall, combining these two metrics into a single measure to provide a comprehensive assessment of model performance [57]. Several metrics were used in the 20 reviewed studies. Though F1-scores and accuracy appeared in the same number of studies, F1-scores had more recordings than accuracy. Table 4 highlights various metrics and their corresponding frequencies, used to evaluate the performance of AI/ML approaches in the reviewed studies.

Based on availability, consistency, accuracy, completeness, and relevancy, Supplementary Material: SM S9 was generated to show the data that were captured for meta-analysis. The F1-scores from the nine studies considered for meta-analysis and the different AI/ML algorithms and models employed in each study resulted in 69 observations being generated, as recorded in Supplementary Material: SM S9.

Table 4. Metric measures used in the reviewed studies.

Metric	Frequency	Rank
F1-Score	9	1
Accuracy	9	1
Sensitivity	8	3
AUC (Area Under the Curve)	7	4
Recall	6	5
Specificity	5	6
PPV (Positive Predictive Value)	4	7
NPV (Negative Predictive Value)	4	7
Precision	4	7
Log-Loss	3	10
Misclassification Rate	1	11
Feature Importance	1	11

3.7.1. Descriptive Analysis

Uses of Artificial Intelligence and Machine Learning Approaches

The meta-analysis findings corroborate the earlier qualitative analysis, confirming that AI/ML approaches were predominantly used for predicting HIV status, HIV infection, virological failure, and HIV outcomes. Additionally, these approaches were employed to identify HIV predictors for screening, develop HIV/AIDS prognostic tools, and diagnose and predict sexually transmitted diseases (STDs).

Sample Sizes and F1-Scores

In the meta-analysis, Table 5 shows that the reviewed studies had a mean sample size of 29,471.67 and a median of 6672, highlighting a significant disparity between the two measures. This suggests that, while some studies had very small sample sizes, others were exceptionally large, reflecting that the distribution of sample sizes across the studies is likely right-skewed, indicating that there are many small studies and only a few very large ones. This skewness may be primarily due to the presence of a few studies with significantly large sample sizes. The sample sizes ranged from a minimum of 400 to a maximum of 87,044, yielding a range of 86,644, which underscores the substantial variability across studies. This variability is further reflected by a standard deviation of 36,363.5, indicating that the sample sizes are widely dispersed within the given range. These findings are confirmed by the box and whisker plot in Figure 5, showing a very wide rectangle in the upper 50% of the sample size data and a narrow rectangle representing the lower 50%.

Table 5. Descriptive statistics.

Statistic	Sample Size	F1-Score
Mean	29,471.67	0.7886
Median	6672	0.811
Minimum	400	0.114
Maximum	87,044	0.993
Standard Deviation	36,363.5	0.163

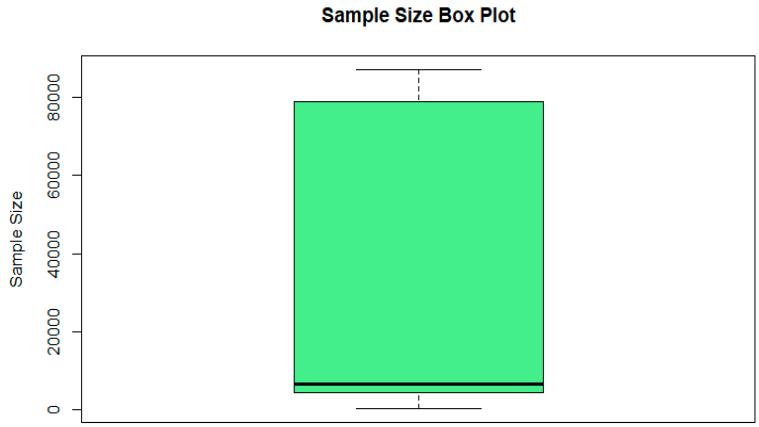


Figure 5. Box and whisker plot for the sample sizes.

In addition, the mean F1-score was 0.7886, and a median of 0.811 showed a small difference between the two metrics. However, the minimum F1-score was 0.114, highlighting the poor performance of AI/ML approaches in some studies, and the maximum was 0.993, reflecting the good performance of AI/ML approaches in some of the reviewed studies, giving a range of 0.879. A standard deviation of 0.163 may reflect that there are mild differences among the F1-scores. These findings are summarized in the box and whisker plot in Figure 6, showing almost symmetrical data with the lower and upper 50% of the F1-scores, occupying almost equal spaces in the box. The box plot shows that there are about five outliers in the F1-scores, shown by the dots below the lower whisker.

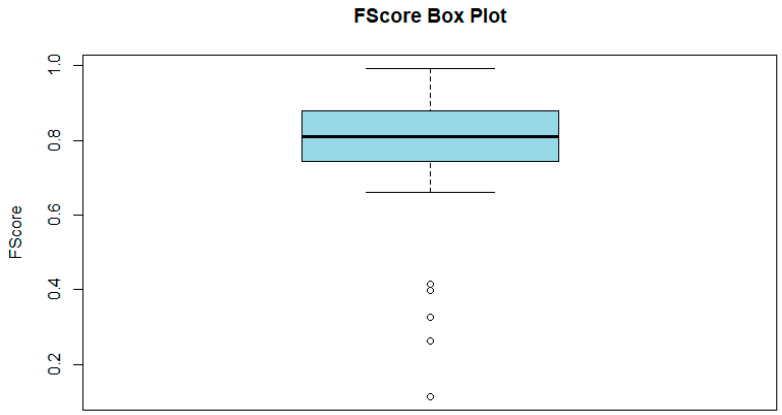


Figure 6. Box and whisker plot for the F1-scores.

The quantitative variables, sample size, and F1-score were assessed for any relationships or associations. The scatter plot in Figure 7 does not show a clear pattern of the relationship between F1-scores and sample size. It shows that AI/ML approaches performed well with small samples, and they also performed poorly with small samples to a lesser extent. Similarly, most of the AI/ML approaches performed well with large samples except for two studies that had F1-scores below 0.5. The absence of a clear trend or pattern may imply that AI/ML approaches' performance may be influenced by other factors, not necessarily the sample size.

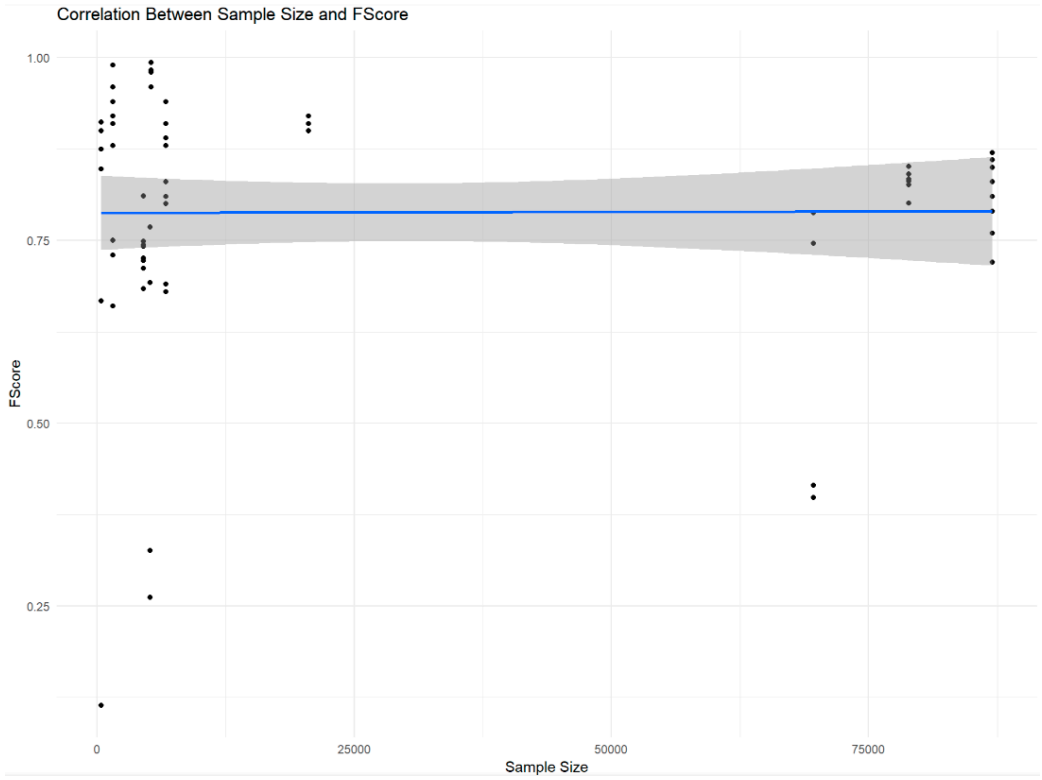


Figure 7. F1-scores—sample sizes scatter plot.

Effects Modelling

The mixed-effects regression model: funnel plot asymmetry.

A regression test for funnel plot asymmetry was conducted for the mixed-effects regression model to test the potential of publication bias or other small-study effects in the meta-analysis. The test was conducted at a 5% (0.05) level of significance, testing the following hypotheses:

H_0: $\beta = 0$ (there is no asymmetry in the funnel plot, i.e., the regression coefficient of the predictor is equal to zero).

H_1: $\beta \neq 0$ (there is an asymmetry in the funnel plot, i.e., the regression coefficient of the predictor is not equal to zero).

The test yielded z = 0.0117, p = 0.9906, limit estimate (as sei→0): b = 0.7247 (95% CI: −9.4763, 10.9256). A p-value of 0.9906 is much larger than 0.05; we failed to reject the null hypothesis, concluding that there is no significant evidence of asymmetry in the funnel plot. This suggests no indication of publication bias or small-study effects at the 5% significance level. The limit estimate (as sei→0) was b = 0.7247, and the confidence interval, (95% CI: −9.4763, 10.9256) supports the existence of significant uncertainty that may be due to heterogeneity or variation across reviewed studies. However, the wide CI raises concerns that may need further investigation. These findings are presented in Figure 8, where most of the standard errors were equal to zero or close to zero. The funnel plot, which plotted the standard error (precision) against the observed F1-scores, showed that all points were centered on or near the vertical line at zero. This symmetry further supports the conclusion of minimal evidence for publication bias, with observed outcomes appearing consistent across studies, regardless of their precision or sample size variability.

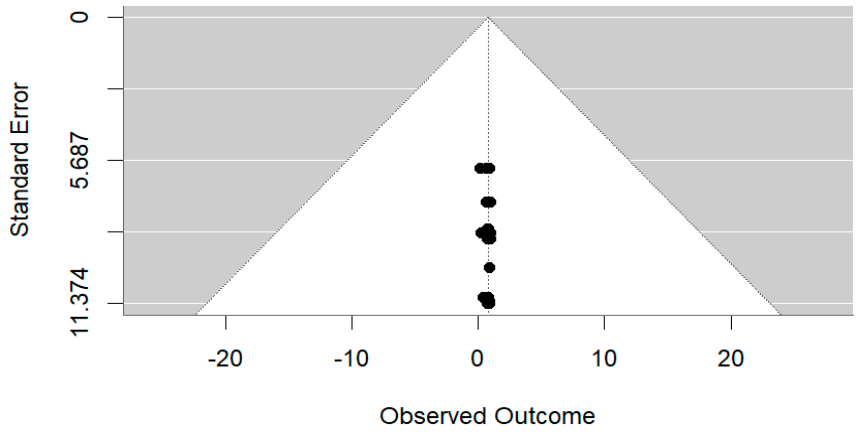


Figure 8. Funnel plot asymmetry.

The meta-analysis enabled the common effects and the random effects models to be conducted, see Table 6, yielding a pooled effect size of 0.7897 (95% CI: 0.7883, 0.7910) under the common effects model and 0.7889 (95% CI: 0.7511, 0.8268) under the random effects model. Both models supported a common effect size of 0.79, supported by a *p*-value of zero in both cases, indicating that the effect size was statistically significant.

Table 6. Common and random effects model results.

Model	SMD	95% CI	z	*p*-Value
Common effects model	0.7897	[0.7883, 0.7910]	1126.07	0
Random effects model	0.7889	[0.7511, 0.8268]	40.82	0

Standardized Mean Differences

An I^2 statistic of 99.8% in Table 7 indicates an extremely high heterogeneity, suggesting large variations between studies with a limited contribution from the random sampling error. This is further supported by the tau-squared (τ^2) estimate of 0.0254 (95% CI: 0.0187, 0.0376), showing significant variance across studies. The heterogeneity test, conducted at a 5% significance level, produced a Q statistic of 29,682.28 (df = 68, *p*-value = 0), confirming that the observed variability is less likely to be due to chance.

Table 7. Heterogeneity assessments.

Quantifying Heterogeneity	Tau-squared (τ^2) = 0.0254	95% CI [0.0187, 0.0376]
	Tau (τ) = 0.1594	[0.1368; 0.1939]
	I^2 *statistic* = 99.8%	
Test of Heterogeneity	Q = 29,682.28	df = 68
	p-value = 0	

Forest Plot

A forest plot was constructed to summarize the meta-analysis data. The forest plot shows that the AI/ML approaches demonstrated reliable performance, as confirmed by most F1-scores that were close to 0.8 and restricted confidence intervals of widths ranging from 0.02 to 0.06 being the widest. Most studies had a width of 0.02; a few studies, for instance [55], had a wider confidence interval of 0.06 with corresponding lower F1-scores, suggesting poor performance of AI/ML approaches. The overall F1-score across studies is much higher than the baseline, assuming a threshold of 0.5, as proven by the pooled

effect size that is represented by the diamonds lying to the right of the reference line. The diamonds' small widths show low variability and high precision in the pooled effect size. In this regard, large studies, for instance [42,48,52] contributed more to the pooled effect, because they also carried greater weights. The opposite is also true. The study by [54], with F1-scores below 0.5, contributed less to the pooled effect because of its lesser weight and wider confidence intervals, reflecting poor performance and high uncertainty. In brief, the forest plot reflects that most of the AI/ML approaches showed good performance across the reviewed meta-analysis studies regardless of the data irregularities. Note that, the presence of outliers and large variations in the sample size and F1-score data indicated the need for transformation before further analysis. A log transformation was applied to the data, and the results were summarized in a forest plot for the meta-analysis in Figure 9.

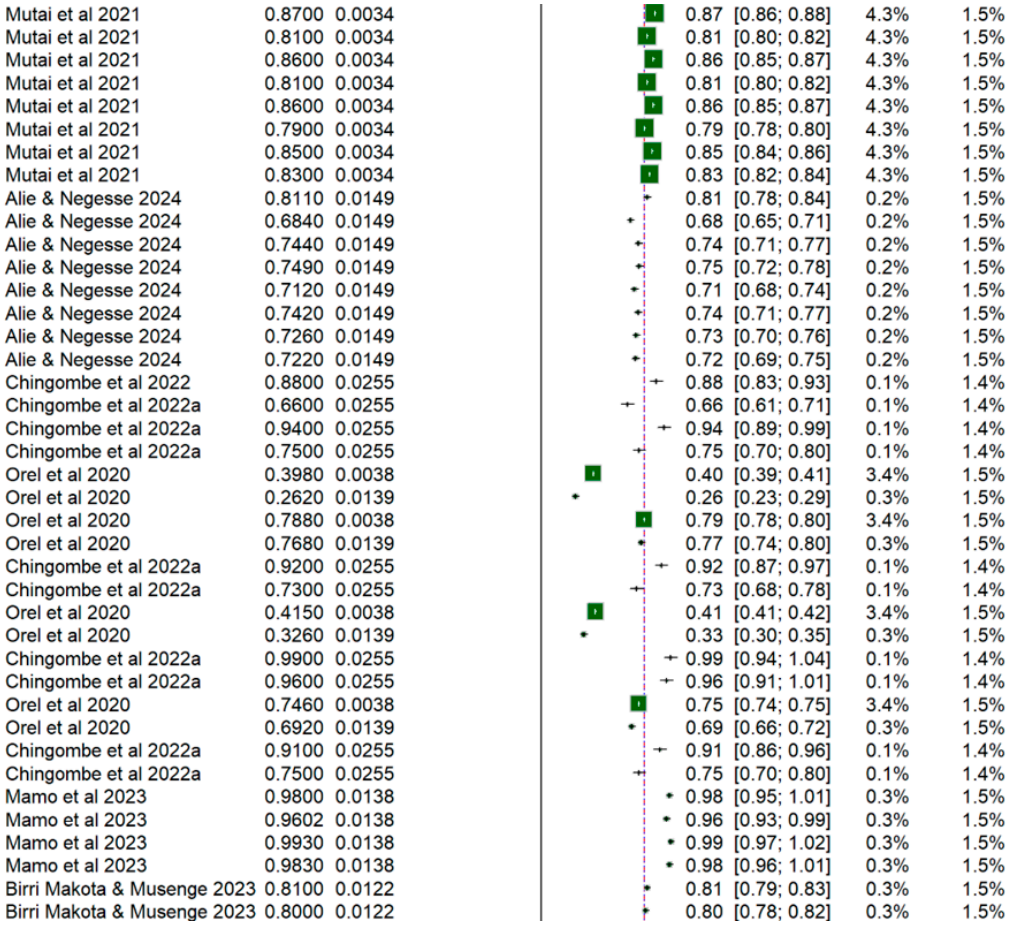


Figure 9. Forest plot [39,42,44,45,48,52,54].

3.7.2. Subgroup Analyses

To better understand and explain the high heterogeneity, additional subgroup analyses based on SSA subregions were conducted to explore potential sources of variability. A comparison of the AI/ML approaches' performance according to SSA subregions was carried out by conducting a clustering analysis. The clustering analysis of regions based on F1-scores and mean sample sizes reveals a significant variation in model performance and data availability across SSA. The cluster plot in Figure 10 shows that the AI/ML approaches' performance can be subdivided into three clusters. Southern Africa, represented by Cluster 2, demonstrates the highest F1-scores and the largest mean sample sizes, indicating robust model performance and substantial data availability. East Southern Africa, part of Cluster 1 along with West Africa, is characterized by large sample sizes but relatively low F1-scores,

suggesting that, despite substantial data resources, model performance in this region is limited. West Africa, also in Cluster 1, exhibits both small sample sizes and low F1-scores, implying challenges in both data availability and model accuracy. East Africa, included in Cluster 3, shows moderate F1-scores and sample sizes, reflecting balanced but less optimal performance compared to Southern Africa. These findings highlight Southern Africa as the best-performing region, with East Southern Africa's performance limited by low F1-scores, despite large samples, emphasizing the need for improved data collection and model performance in regions like West Africa.

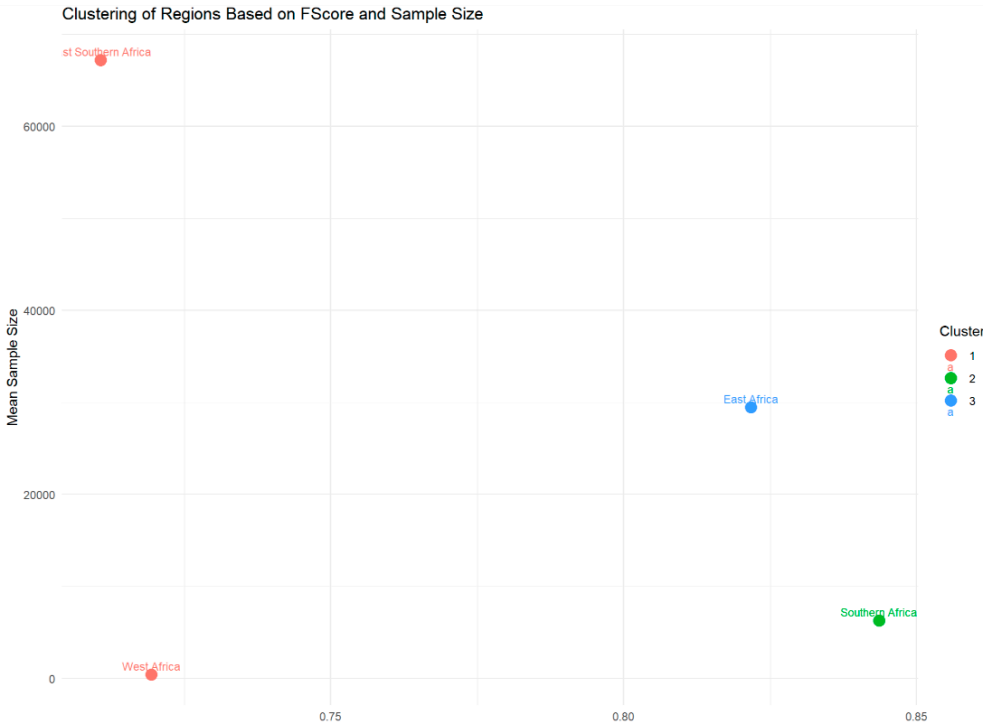


Figure 10. Cluster plot.

A comprehensive and robust subgroup analysis according to regions was conducted through the Kruskal–Wallis test and ANOVA, see Table 8. This was important to leverage the complementary strengths of these tests. The Kruskal–Wallis test helped to handle skewed data with outliers and violations of normality assumptions for nonparametric analysis. The ANOVA helped with addressing normality and homogeneity assumptions for parametric analysis. The researcher adopted both tests to allow for cross-validation of findings for credible and valid conclusions. The Kruskal–Wallis test for F1-scores yielded a test statistic H = 6.5859 with a *p*-value of 0.0862, indicating insufficient evidence at the 5% significance level to reject the null hypothesis. This suggests that there are no significant differences among the F1-scores across the regions of SSA. However, the ANOVA for F1-scores yielded a *p*-value of 0.0228, providing significant evidence of meaningful differences among the regions. Post hoc analysis using Dunn's test further identified a significant difference in F1-scores, specifically between Southern Africa and East Southern Africa ($p = 0.0314$), aligning with the ANOVA results. Thus, while most SSA subregions show no major differences in F1-scores, significant differences exist between Southern Africa and East Southern Africa. Southern Africa consistently showed stronger performance in F1-scores compared to East Southern Africa, implying the need for further investigation into the specific factors contributing to these differences. The Kruskal–Wallis test and ANOVA for sample sizes yielded *p*-values = 0.000, supporting significant evidence of differences in sample sizes among the regions in SSA, and this aligned with the post hoc analysis

using Dunn's test, which showed sample size differences between East Southern Africa and Southern Africa, East Africa and West Africa, East Southern Africa and West Africa, Southern Africa and West Africa, East Africa and East Southern Africa, and East Africa and Southern Africa. This confirms strong variability in sample sizes across the SSA regions. The correlation between F1-scores and sample sizes yielded r = 0.0055 with a *p*-value of 0.9643, suggesting a lack of evidence to support a linear relationship between F1-scores and sample sizes.

Table 8. Subgroup analyses tests and results.

Test	Statistic	*p*-Value	Conclusion
Kruskal–Wallis test for F1-scores	H = 6.5895	0.0862	Fail to reject the null hypothesis
Kruskal–Wallis test for sample sizes	H = 34.6	0.000	Reject the null hypothesis
ANOVA for F1-scores	-	0.0228	Reject the null hypothesis
ANOVA for sample sizes	F = 23.68	0.000	Reject the null hypothesis
Dunn's test for F1-scores	0.0314 (Southern Africa vs. East Southern Africa		Reject the null hypothesis
Dunn's test for F1-sample sizes	*p*-value < 0.05 (East Southern Africa vs. Southern Africa; East Africa vs. West Africa; East Southern Africa vs. West Africa; Southern Africa vs. West Africa; East Africa vs. East Southern Africa; East Africa vs. Southern Africa)		Reject the null hypothesis
Dunn's test for F1-sample sizes		1 East Africa vs. Southern Africa	Fail to reject the null hypothesis
Correlation between F1-scores and sample sizes	r = 0.0055	0.9643	Fail to reject the null hypothesis

4. Discussion

The systematic review and meta-analysis sought to explore the application of AI technologies in improving STI diagnosis and management, as well as to describe associated successes and gaps in SSA. Among the 49 countries in SSA, only 20 (41%) have adopted AI approaches for diagnosing and managing STIs. Southern Africa demonstrated the highest adoption rate at 80%, followed by East Africa at 40%, West Africa at 33%, and Central Africa at 11%. These findings align with other studies [58,59], highlighting the unequal availability and access to technology globally. Developing countries, particularly in SSA, lag in adopting AI technologies, while developed nations benefit from an abundance of these advancements [59,60]. The current study advocates for the adoption of AI approaches in SSA, given that the region bears the highest burden of STIs, particularly HIV [61–64].

Southern and East Africa's higher representation in AI applications reflects ongoing efforts in regions hardest hit by STIs and HIV [65,66]. This aligns with findings [37,67–71] that countries like Ethiopia, Kenya, South Africa, Uganda, and Zimbabwe have integrated AI approaches into data analysis to address high STI and HIV prevalence. Similarly, West African countries, such as Côte d'Ivoire, Nigeria, and Sierra Leone, are also making strides in adopting AI technologies due to their significant STI burden [49,68,72]. Central Africa, however, remains far behind, with Cameroon being the only country represented in the reviewed studies, consistent with findings from [73].

The data originate from diverse sources, including population-based assessments (e.g., DHS), community surveys, health facility records, bio-behavioral HIV data, rapid HIV test images, specific population studies, and purchasing data for sexual health products. This diversity enriches AI applications by providing multi-dimensional insights but poses challenges in harmonization and integration due to differences in type, scale, and focus [74]. While large-scale datasets, like DHS, offer generalizable insights, smaller datasets provide depth and specificity. Heterogeneity requires robust preprocessing and

standardization to ensure accuracy and reliability, and biases must be managed to avoid skewed AI outcomes [75]. Algorithmic bias in healthcare happens because datasets are not created equally. The risk of algorithmic bias in healthcare stems from systemic inequalities in dataset curation, disparities in opportunities for participation in research, and inequitable access to healthcare services [76]. These challenges can result in datasets that inadequately represent diverse populations, leading to biased AI models and suboptimal outcomes for underrepresented groups [77]. By addressing these challenges, rich and varied data can effectively support robust and unbiased AI-driven solutions.

The study highlights the effectiveness of various AI and ML methods in managing HIV and STIs through detection, diagnosis, treatment, and monitoring. Algorithms such as random forest, AdaBoost, GradBoost, XGBoost, K-nearest neighbors, and support vector machines have proven valuable for disease prediction, particularly in identifying high-risk individuals to target prevention efforts [78,79]. Decision trees, multilayer perceptions, and logistic regression models are also effective for disease prediction and management [80]. Moreover, advanced methods, such as decision trees (J48), LASSO models, and DL approaches, aid in diagnosing and predicting STIs, addressing infection risks, tracking hotspots, and analyzing community spread [81–83]. Applications in image analysis, STI testing, and counseling have significantly improved diagnostic and treatment access, consistent with broader applications in medicine [84–89]. Artificial intelligence's role in point-of-care diagnosis, test interpretation, and outbreak management supports hospital activities and clinical decision-making [90,91].

Despite these advancements, SSA faces challenges in adopting WHO-recommended, molecular-based STI testing due to a lack of accessible, accurate, and affordable diagnostic tools [7]. Syndromic management remains widely used yet fails to address approximately 70% of asymptomatic curable STIs, increasing untreated risks [87,88,92]. Integrating ML, big data analytics, and statistical approaches could enable personalized, predictive, and preventative healthcare through electronic health records for STIs [89]. These advancements could help SSA achieve the UNAIDS 95-95-95 targets to end the HIV epidemic by 2030.

However, implementing AI technologies in healthcare faces several challenges. The absence of technical guidelines, regulatory frameworks, and skilled personnel creates uncertainty [85,87]. These challenges are compounded by unreliable health data, model specification issues, and insufficient clinician expertise [93–96]. Privacy, security concerns, and the involvement of diverse stakeholders further complicated implementation. In SSA, limited access to large datasets necessary for AI predictions using supervised modeling is hindered by inadequate data collection infrastructure and a lack of standardization in data formats [93,94].

While countries like South Africa have embraced AI technologies, many SSA nations face barriers, such as poverty, unemployment, and inadequate policy frameworks [97–99]. Limited collaboration between public and private sectors and a lack of data repositories further hinder progress [100]. Advanced techniques, like NLP, CNNs, and AI-driven drug discovery, remain underutilized in SSA. In contrast, regions like North America and Europe employ these methods to enhance the diagnosis and management of diseases, including STIs [101–105]. Bridging this technological gap through international collaboration and capacity building is critical for SSA to leverage advanced AI/ML technologies effectively.

Despite these challenges, AI/ML holds promise for improving care, reducing costs, and supporting the management of infectious diseases, like HIV and STIs [96,106]. By moving beyond syndromic management, SSA can embrace ML and big data analytics to make informed decisions, achieve UNAIDS targets, and advance precision medicine [107–110]. African governments and international partners must invest in robust STI diagnosis and management systems to realize the full potential of 4IR technologies [62,63].

The finding that all reviewed studies were methodological underscores the early-stage development of AI methods in STI diagnosis and management within SSA [111]. This reflects a significant focus on model development and evaluation, highlighting AI's potential to address public health challenges. However, the absence of real-world testing emphasizes the need for further research to understand how these methods perform in diverse clinical and community settings.

5. The Implications of AI Approaches in STI Diagnosis and Management

This study provides practical application of AI technologies in diagnosing, treating, and managing STIs across SSA which are often overlooked. Understanding this has the potential to improve sexual health outcomes, address gaps in STI diagnosis, and surpass the limitations of traditional syndromic management approaches. Traditional diagnostic, prognostic, and therapeutic procedures for addressing STIs in SSA have often lacked accuracy, speed, and accessibility. The integration of AI technologies in STI diagnosis and management offers promising solutions to overcome these challenges. However, SSA's high rates of STI/HIV, limited resources, skilled personnel shortages, and the slower adoption of technology underscore the need for collaboration between SSA governments, developed regions, non-governmental organizations, and the international community. Such partnerships could accelerate the development of the resources and infrastructure required to effectively implement AI technologies in SSA's healthcare sector, while exchange programs and training initiatives would help build local capacity.

Future research should prioritize the transition from methodological advancements to real-world validation in clinical environments. This shift is critical for assessing AI methods' practical utility, scalability, and impact in improving STI diagnosis and management in SSA. By addressing these gaps, researchers can help ensure AI methods achieve their full potential and contribute meaningfully to public health outcomes. Further research should validate AI and ML applications for STI diagnosis and management in real-world SSA settings, exploring ethical considerations and ensuring the relevance and efficiency of these technologies across diverse communities. Comprehensive datasets capturing relevant population characteristics are essential to drive informed decision-making and guide policy. These findings have implications for STI and HIV management in SSA, affecting both key and general population. Stakeholders, including governments, private organizations, and healthcare providers, must prioritize accurate, timely information to enhance health outcomes. Policymakers and practitioners should review existing policies, supported by monitoring and evaluation frameworks, to improve STI care. Collaboration among healthcare providers, community organizations, and policymakers will be vital to overcoming resource constraints, cultural barriers, and social determinants of health, ultimately promoting sexual health across the region.

6. Strengths and Limitations

The main strength of this study is that it is current and relevant to the SSA community. The findings of this study provide new knowledge that can form a basis to inform the policy and practice of STI and HIV diagnosis, prevention, and management. However, the study may be limited in that only those publications and documents accessible to the researchers were used, and there may be new findings since research is always taking place.

There are data inadequacies due to a lack of consideration or absence of certain characteristics, such as not explaining the effects of missing sociodemographic attributes of the participants, behavioral characteristics, and not emphasizing certain health issues. In addition, some of the studies had procedural limitations, including using smaller samples, focusing on very few algorithms, insufficient assessment of model performance, and limited

scope. There were limitations on study designs that restricted the generalizability of the study findings, such as the use of secondary data without the integration of AI approaches in primary healthcare settings.

The implications of right-skewed distribution for meta-analysis results are noteworthy. Larger studies may have a disproportionate influence on the pooled effect size because of their greater weight in the analysis. Meanwhile, smaller studies may contribute less to the overall findings, even though they can represent important subpopulations. In future scenarios where a right-skewed distribution occurs, it would be beneficial to conduct a sensitivity analysis. This analysis can assess whether excluding the largest studies significantly alters the results, helping to determine if the findings are robust against the influence of potential outliers.

7. Conclusions

In conclusion, SSA holds significant potential to leverage AI technologies for the diagnosis, identification, treatment, and management of STIs. Artificial intelligence and ML approaches offer promising opportunities for point-of-care diagnostics, interactive conversational agents for patient engagement, and the facilitation of targeted curative therapy. These technologies can enhance patient outcomes across various phases of healthcare and enable personalized medicine and care. Integrating AI models into healthcare applications provides essential support for healthcare professionals and policymakers in disease diagnosis, management, and decision-making processes.

However, several challenges hinder the widespread adoption of AI-based solutions in SSA. These include biases in AI algorithms, the lack of high-quality health data, the shortages of skilled personnel, and the absence of supportive policies and frameworks. Addressing these barriers is crucial to promote the ethical use of AI/ML and to develop policies that facilitate the integration of AI approaches into SSA's health systems. By overcoming these challenges, AI-based models can transition healthcare systems from traditional methods to smart care, supporting healthcare workers and researchers in advancing personalized and data-driven healthcare.

This review underscores the critical need to move beyond methodological studies and advance AI methods in STI diagnosis and management to real-world implementation. While methodological studies highlight the significant potential of AI technologies, their reliance on simulation and theoretical settings emphasizes the urgent need for practical validation. Implementation-based research is essential to evaluate the applicability, scalability, and impact of AI methods in clinical environments. This transition is vital to ensure that AI approaches contribute effectively to improving STI diagnosis and management in real-world settings and to addressing the future research needs of AI approaches in healthcare.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/a18030151/s1, SM S1: PRISMA Checklist of items to include when reporting a systematic review or meta-analysis; SM S2: Critical Appraisal Skills Programme (CASP) Checklist of a systematic review; SM S3: Tripod and AI Checklist; SM S4: Cochrane Risk of Bias Tool for Randomized Controlled Trials; SM S5: Newcastle-Ottawa Quality Assessment Form for Cohort Studies; SM S6: Sample of the search strategy; SM S7: Data extraction tool; SM S8: Quality and bias assessment; SM S9: Extracted data for meta-analysis [37–56].

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