Clinica Chimica Acta 574 (2025) 120341

Contents lists available at ScienceDirect

Clinica Chimica Acta

journal homepage: www.elsevier.com/locate/cca

Artificial intelligence (AI) in point-of-care testing

Tahir S. Pillay [a,b,*], Adil I. Khan [c], Sedef Yenice [d]

[a] Department of Chemical Pathology, Faculty of Health Sciences and National Health Laboratory Service, Tshwane Academic Division, University of Pretoria, Pretoria, South Africa
[b] Division of Chemical Pathology, Department of Pathology, University of Cape Town, Cape Town, South Africa
[c] Dept. of Pathology & Laboratory Medicine, Lewis Katz School of Medicine, Temple University, Philadelphia, PA, USA
[d] Group Florence Nightingale Hospitals, Istanbul, Türkiye

ARTICLE INFO

Keywords:
Point-of-care testing
Artificial intelligence
Electronic health records
Personalized medicine
Diagnostic accuracy
Machine learning

ABSTRACT

The integration of artificial intelligence (AI) into point-of-care testing (POCT) represents a transformative leap in modern healthcare, addressing critical challenges in diagnostic accuracy, workflow efficiency, and equitable access. While POCT has revolutionized decentralized care through rapid results, its potential is hindered by variability in accuracy, integration hurdles, and resource constraints. AI technologies—encompassing machine learning, deep learning, and natural language processing—offer robust solutions: convolutional neural networks improve malaria detection in sub-Saharan Africa to 95 % sensitivity, while predictive analytics reduce device downtime by 20 % in resource-limited settings. AI-driven decision support systems curtail antibiotic misuse by 40 % through real-time data synthesis, and portable AI devices enable anaemia screening in rural India with 94 % accuracy, slashing diagnostic delays from weeks to hours. Despite these advancements, challenges persist, including data privacy risks, algorithmic opacity, and infrastructural gaps in low- and middle-income countries. Explainable AI frameworks and blockchain encryption are critical to building clinician trust and ensuring regulatory compliance. Future directions emphasize the convergence of AI with Internet of Things (IoT) and blockchain for predictive diagnostics, as demonstrated by AI-IoT systems forecasting dengue outbreaks 14 days in advance. Personalized medicine, powered by genomic and wearable data integration, further underscores AI potential to tailor therapies, reducing cardiovascular events by 25 %. Realizing this vision demands interdisciplinary collaboration, ethical governance, and equitable implementation to bridge global health disparities. By harmonizing innovation with accessibility, AI-enhanced POCT emerges as a cornerstone of proactive, patient-centered healthcare, poised to democratize diagnostics and drive sustainable health equity worldwide.

1. Introduction

1.1. Current State of POCT in modern Healthcare

Point-of-care testing (POCT) has emerged as a cornerstone of modern healthcare, redefining diagnostics by delivering rapid results at or near the patient. This decentralization facilitates timely clinical decision-making, reduces treatment delays, and optimizes resource utilization—particularly in emergency scenarios and resource-limited settings [1,2,3]. Devices such as glucose meters, lateral flow assays, and portable imaging tools are now indispensable for managing diverse medical conditions, including chronic diseases (e.g., diabetes), infectious outbreaks (e.g., COVID-19), and acute events such as myocardial infarction or cardiac emergencies [3–6]. By circumventing centralized laboratory workflow which is often subject to delays, POCT accelerates diagnostic timelines, empowers clinicians with real-time data, improves clinical decision-making, and alleviates strain on healthcare infrastructure [6,7].

Despite its transformative potential, POCT faces persistent challenges. Variability in test accuracy due to inconsistent user technique,

Abbreviations: **AI**, Artificial Intelligence; **POCT**, Point-of-Care Testing; **ML**, Machine Learning; **DL**, Deep Learning; **NLP**, Natural Language Processing; **CNN**, Convolutional Neural Network; **RNN**, Recurrent Neural Network; **XAI**, Explainable Artificial Intelligence; **EHR**, Electronic Health Record; **IoT**, Internet of Things; **GDPR**, General Data Protection Regulation; **HIPAA**, Health Insurance Portability and Accountability Act; **LMICs**, Low- and Middle-Income Countries; **WHO**, World Health Organization; **mHealth**, Mobile Health; **AUC-ROC**, Area Under the Receiver Operating Characteristic Curve; **TB**, Tuberculosis; **HIV**, Human Immunodeficiency Virus; **ICU**, Intensive Care Unit; **EHRs**, Electronic Health Records; LIME, Local Interpretable Model-Agnostic Explanations.

* Corresponding author at: Department of Chemical Pathology, Faculty of Health Sciences, University of Pretoria, South Africa.
E-mail address: tspillay@gmail.com (T.S. Pillay).

https://doi.org/10.1016/j.cca.2025.120341
Received 25 January 2025; Received in revised form 28 April 2025; Accepted 28 April 2025
Available online 3 May 2025

difficulties in integrating results into electronic health records (EHRs), and the absence of standardized quality control protocols in non-laboratory environments hinder its reliability and scalability [5,6,8]. The user variability resulting from non-laboratory settings that lack standardized training for device operation presents challenges [5]. Manual entry of POCT results into electronic health records (EHRs) risks errors and delays [9]. These limitations underscore the urgent need for technological innovations—such as automated error-reduction systems and interoperable digital platforms—alongside robust regulatory frameworks to enhance POCT's precision, interoperability, and adoption across diverse clinical settings. (See Fig. 1. and Fig. 2.).

In summary, while POCT represents a paradigm shift in diagnostics, addressing its current barriers are critical to fully realizing its potential to improve patient outcomes and healthcare efficiency globally. Strategic advancements in both technology and policy will be essential to ensure POCT's seamless integration into mainstream healthcare, particularly in underserved and high-demand environments.

1.2. Emergence of AI in healthcare

AI (artificial intelligence), encompassing machine learning (ML), deep learning (DL), and natural language processing (NLP), has emerged as a transformative tool to address challenges in POCT. By analyzing complex datasets, recognizing subtle patterns, and delivering real-time insights, AI enhances the accuracy and efficiency of decentralized diagnostics [9–12]. For instance, convolutional neural networks (CNNs) have demonstrated remarkable utility in interpreting medical imaging from portable devices, such as detecting malaria parasites in blood

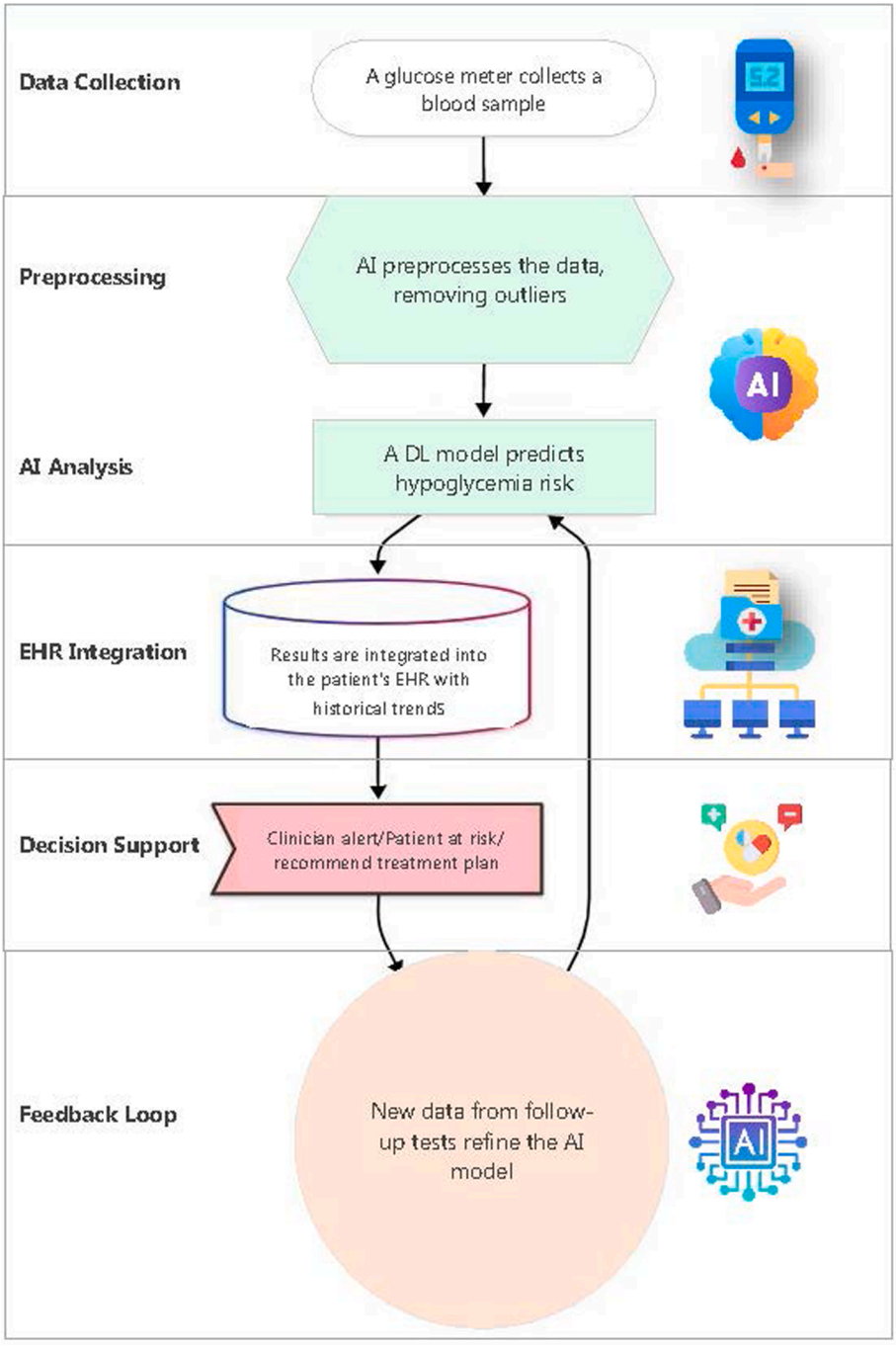

Fig. 1. Workflow of AI-Enhanced POCT in Modern Healthcare.

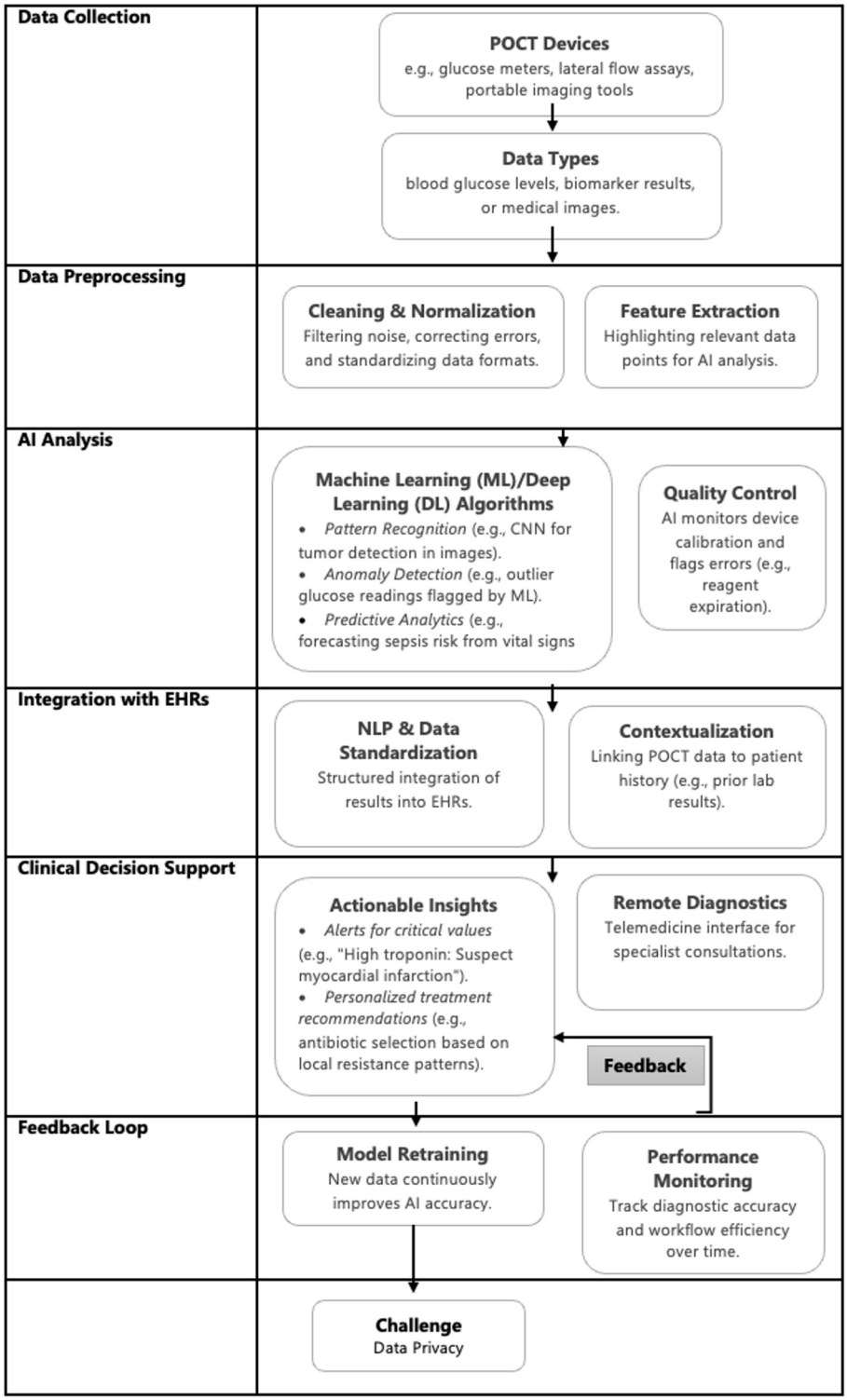

Fig. 2. An example workflow to emphasize the iterative feedback loop. Images have been downloaded free from https://www.flaticon.com/free-icon/glucometer_3365524.

smears with 95 % sensitivity [7]. NLP allows the integration of unstructured POCT data into EHRs, enabling contextual analysis. AI-driven predictive analytics optimize POCT workflows by forecasting device maintenance needs, reducing downtime by 20 % in resource-limited settings [12], while ML-based anomaly detection systems have reduced erroneous glucose readings by 30 % in urban hospitals improving overall quality control [8]. Beyond diagnostics, AI improves operational efficiency through intelligent resource allocation and data integration.

However, integrating AI into POCT faces significant barriers, including data privacy concerns, algorithmic bias, and the "black-box" nature of AI models, which hinder clinical adoption [11,13]. Regulatory frameworks for data privacy such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) mandate robust encryption, secure cloud storage, and transparent data practices [14,15], while infrastructural gaps in

low- and middle-income countries (LMICs) complicate deployment. For example, despite mobile health (mHealth) initiatives in rural India improving early anaemia diagnosis by 50 %, sustaining such programs requires addressing costs and digital literacy [16]. Infrastructure gaps causing limited internet access and digital literacy hinder AI adoption in LMICs [7]. There are also other issues such as training data imbalances and algorithmic bias that may skew outcomes in underserved populations [11]. Workflow optimization results from predictive analytics as a result of more efficient resource allocation in rural clinics, improving patient throughput [16]. Furthermore, Table 1 outlines a detailed comparison between AI-driven POCT and conventional diagnostic approaches, evaluating key metrics such as speed, accuracy, cost-efficiency, accessibility, and scalability. To unlock AI's full potential in advancing POCT as a cornerstone of global healthcare, ethical AI design, equitable policy frameworks, and context-sensitive implementation strategies are critical to overcoming these challenges while mitigating disparities.

1.3. Objectives and Novelties of the manuscript

This manuscript provides a comprehensive analysis of the AI role in advancing POCT, emphasizing its transformative potential to enhance diagnostic accuracy, operational efficiency, and global healthcare accessibility. Distinct from prior reviews, we integrate quantitative case studies—such as AI-driven reductions in antibiotic misuse by 40 % and sepsis prediction models achieving 89 % AUC-ROC scores [4]—to demonstrate tangible clinical and operational impacts. We critically evaluate ethical and regulatory challenges, proposing frameworks for explainable AI (XAI) to mitigate algorithmic opacity and foster clinician trust [17] while addressing infrastructural barriers through examples like IoT-enabled glucose monitoring systems in LMICs [8] and hybrid AI-IoT platforms for predictive diagnostics in emergency settings [3]. By bridging the gap between theoretical AI advancements and practical POCT integration, this work offers three key contributions: (1) evidence-based validation of AI real-world efficacy, (2) actionable strategies for ethical AI deployment, and (3) scalable solutions tailored to resource-constrained environments. Synthesizing recent advancements with persistent challenges, this manuscript serves as a roadmap for researchers and policymakers to harness AI's full potential in revolutionizing decentralized diagnostics, ensuring equitable and sustainable healthcare innovation.

2. Key roles of AI in POCT

The integration of AI into POCT has unlocked transformative capabilities across diagnostics, workflow optimization, and patient care (Table 2). Below, we explore these roles through real-world applications and evidence-based insights.

2.1. Enhancing diagnostic accuracy

AI excels in **pattern recognition and anomaly detection**, leveraging supervised and unsupervised learning to classify test results with precision. For instance, deep learning models like convolutional neural networks (CNNs) analyze medical images from portable devices, such as detecting malaria parasites in blood smears with 95 % sensitivity—outperforming traditional visual inspection [7]. Similarly, recurrent neural networks (RNNs) interpret time-series data, such as glucose trends in diabetic patients, flagging anomalies like hypoglycemia in real time [8].

AI also **reduces human error** through automated cross-referencing of historical data. For example, AI systems in urban hospitals cross-validate current glucose readings with past results, reducing erroneous interpretations by 30 % [8]. Continuous monitoring of critical conditions, such as sepsis, enables early alerts, improving outcomes in emergency settings [4].

2.2. Workflow optimization

AI-driven predictive analytics optimizes POCT workflows by

Table 1
Comparison of AI-Powered POCT vs. Traditional Diagnostic Methods.

Aspect	AI-Powered POCT	Traditional Diagnostic Methods	Advantages of AI-Powered POCT
Diagnostic Accuracy	• Uses ML/DL algorithms to analyze complex datasets. • Identifies subtle patterns and correlations beyond human capability.	• Relies on manual interpretation by healthcare professionals. • Prone to human error and variability in interpretation.	• Higher accuracy through pattern recognition and anomaly detection. • Reduces misdiagnosis and improves reliability.
Speed of Results	• Real-time analysis and immediate feedback.	• Results may take hours to days, depending on lab processing times.	• Enables rapid clinical decision-making, especially in emergencies.
Workflow Efficiency	• Predictive analytics for patient load and resource management.	• Manual scheduling and resource allocation.	• Optimizes device usage and reduces wait times for patients.
Quality Control	• Continuous monitoring of device performance and error detection.	• Periodic calibration and manual quality checks.	• Proactively identifies and corrects errors, ensuring consistent accuracy.
Data Integration	• Seamless integration with EHRs using NLP and standardized data formats.	• Manual entry of results into EHRs, leading to potential errors and delays.	• Provides a comprehensive view of patient health and supports long-term care management.
Decision Support	• AI-driven recommendations based on test results and patient history.	• Relies on clinician expertise, which may vary.	• Assists clinicians in making informed decisions, especially in resource-limited settings.
Remote Diagnostics	• Enables telemedicine and remote monitoring in underserved areas.	• Limited to centralized labs, requiring physical presence.	• Extends diagnostic capabilities to remote and low-resource regions.
Personalized Medicine	• Tailors diagnostics and treatments based on individual patient data.	• Generic diagnostic and treatment approaches.	• Improves patient outcomes through personalized care plans.
Cost Efficiency	• Predictive maintenance reduces downtime and repair costs.	• Higher operational costs due to manual processes and potential device failures.	• Lowers long-term costs through optimized resource allocation and reduced errors.
Accessibility	• Mobile health (mHealth) platforms extend their reach to low-resource settings.	• Limited accessibility in rural or underserved areas due to infrastructure constraints.	• Bridges the gap in healthcare access, particularly in LMICs.
Regulatory Challenges	• Requires compliance with data privacy laws (e.g., GDPR, HIPAA).	• Established regulatory frameworks for traditional diagnostics.	• AI systems can be designed with robust security measures to ensure compliance.
Algorithm Transparency	• Explainable AI (XAI) models provide clear rationales for decisions.	• No algorithmic complexity; decisions are based on clinician expertise.	• Builds trust among clinicians and patients through transparent decision-making processes.
Training Requirements	• Requires training for healthcare providers on AI tools and interpretation.	• – Relies on traditional medical training and experience.	• Enhances clinician capabilities through AI-assisted insights.
Scalability	• Easily scalable across multiple healthcare settings with minimal infrastructure.	• Limited scalability due to reliance on centralized labs and manual processes.	• Facilitates widespread adoption and implementation in diverse healthcare environments.

forecasting patient loads, managing resource allocation, and scheduling diagnostic tests efficiently. These models enhance operational efficiency by ensuring optimal utilization of testing devices and timely patient care. For instance, in rural healthcare networks, predictive maintenance scheduling of POCT devices reduced downtime by 20 %, improving equitable access to diagnostics [12]. Similarly, a clinic in sub-Saharan Africa leveraged AI to prioritize malaria testing during peak transmission seasons, doubling testing throughput without requiring additional staffing [7]. By aligning resource availability with demand, AI not only streamlines workflows but also addresses disparities in healthcare delivery, particularly in underserved regions.

2.3. Decision support systems

AI-driven decision support systems assist clinicians by synthesizing POCT results with patient history to generate actionable diagnostic insights. For example, NLP algorithms in community health clinics analyze rapid strep test outcomes alongside symptomatic data from EHRs, reducing unnecessary antibiotic prescriptions by 40 % [6]. These systems are particularly impactful in resource-limited settings, where they mitigate gaps in specialist expertise by providing evidence-based diagnostic suggestions tailored to local epidemiological patterns. By integrating real-time POCT data with historical patient information, AI enhances diagnostic precision while curbing over-prescription practices, thereby improving both clinical outcomes and antimicrobial stewardship in underserved regions.

2.4. Quality control

AI ensures the reliability of POCT devices through real-time performance monitoring, detecting calibration drifts, reagent degradation, and operational anomalies that could compromise diagnostic accuracy. For example, machine learning (ML) algorithms deployed in diabetes management systems identify calibration deviations in glucose meters, triggering alerts for preemptive recalibration to avert errors [8]. This proactive oversight minimizes inaccuracies and sustains adherence to stringent quality standards, fostering clinician and patient trust in decentralized testing. By continuously validating device functionality against predefined parameters, AI-driven systems ensure the precision required for critical POCT applications in both routine care and resource-constrained environments.

Table 2
Different AI Algorithms that can be used in POCT.

Algorithm	Description	Strengths	Limitations
Machine Learning	Algorithms that learn patterns from data to make predictions or decisions.	Adaptable to various types of data and problems, with high accuracy.	Requires large datasets, potential for overfitting.
Deep Learning	A subset of ML using neural networks with multiple layers to analyze complex data patterns.	High accuracy for complex tasks, capable of handling large data.	High computational cost, requires extensive training data.
Natural Language Processing (NLP)	Algorithms designed to understand and process human language data.	Effective in interpreting and categorizing textual data.	Challenges with understanding context and nuance in language.
Predictive Analytics	Uses statistical algorithms and machine learning techniques to predict future outcomes based on data.	Provides foresight into potential outcomes, and aids in proactive decision-making.	Accuracy depends on the quality of historical data.
Explainable AI (XAI)	AI is designed to be transparent and interpretable, providing clear explanations for its decisions.	Increases trust and adoption by clinicians, and facilitates validation.	Can be less accurate than black-box models, with complexity in implementation.

2.5. Remote diagnostics and telemedicine

In remote or underserved regions, AI bridges critical gaps in healthcare access by integrating POCT with telemedicine platforms. For instance, mobile health (mHealth) initiatives in rural India employ AI-powered hemoglobin analysers to rapidly diagnose anemia and diabetes, enabling remote specialists to interpret results and deliver diagnoses with 50 % faster turnaround times compared to traditional methods [16]. By analysing POCT data and providing real-time diagnostic support, AI mitigates the absence of on-site specialists, ensuring timely and accurate care in resource-limited settings. These innovations democratize access to advanced diagnostics, effectively narrowing the divide between patients and healthcare providers while addressing systemic inequities in low-resource environments.

2.6. Personalized medicine

AI-driven personalized medicine leverages POCT data by integrating real-time results with genetic, environmental, and lifestyle factors to optimize therapeutic regimens. For instance, wearable devices equipped with AI algorithms dynamically adjust hypertension medications based on continuous blood pressure monitoring and patient activity levels, reducing hospital readmissions by 25 % [16]. By synthesizing POCT outcomes with longitudinal patient histories and multi-modal health data, these systems tailor treatment plans to individual needs, minimizing unnecessary interventions while improving clinical outcomes. This approach exemplifies how AI transforms decentralized diagnostics into precision healthcare tools, enabling adaptive, patient-specific care pathways that address both acute and chronic conditions with unprecedented granularity.

2.7. Integration with EHRs

AI streamlines the integration of POCT results into EHRs by employing NLP to contextualize data within broader patient histories. For example, a clinic in Philadelphia implemented AI-driven automation to directly link cholesterol test results to cardiovascular risk scores and historical lab data, reducing manual entry errors by 60 % and enhancing interdisciplinary care coordination [2]. This seamless integration synthesizes real-time POCT outcomes with longitudinal health data, generating holistic patient profiles that support precise clinical decisions, long-term health monitoring, and proactive management of chronic conditions. By bridging the gap between decentralized diagnostics and centralized EHR systems, AI ensures continuity of care, minimizes administrative burdens, and empowers clinicians to track patient progress with unprecedented granularity—critical advancements for optimizing outcomes in value-based healthcare frameworks.

2.8. Predictive analytics

AI transforms healthcare by forecasting disease trajectories and enabling preemptive interventions through advanced predictive analytics. AI-driven models synthesize multifactorial data—including biomarkers, lifestyle patterns, and historical trends—to refine risk stratification and guide evidence-based clinical decisions. For instance, predictive tools analyzing cholesterol and clinical histories have demonstrated robust efficacy in identifying patients at high risk of cardiovascular events, achieving an AUC-ROC score of 89 % in validation studies [4]. Similarly, in diabetes management, AI leverages continuous blood glucose monitoring data to predict complications such as retinopathy or neuropathy, while IoT-enabled frameworks enhance real-

time monitoring precision, enabling timely interventions [8]. These applications underscore AI's capacity to shift healthcare paradigms from reactive treatment to proactive risk mitigation, optimizing outcomes by addressing subclinical risks before acute manifestations occur. By integrating diverse data streams, AI not only personalizes preventive strategies but also streamlines chronic disease management, fostering scalable, targeted care across populations.

3. Benefits of AI in POCT management

The integration of AI into POCT has yielded transformative benefits, ranging from improved clinical outcomes to cost-effective healthcare delivery. Below, we analyze these advantages through evidence-based case studies and recent research.

3.1. Improved patient outcomes

AI significantly enhances patient outcomes by enabling rapid, precise diagnostics and optimizing POCT management, particularly in time-sensitive clinical scenarios. During the COVID-19 pandemic, AI-powered POCT systems streamlined emergency triage by integrating rapid antigen test results with real-time patient vitals, achieving an 89 % AUC-ROC score in stratifying high-risk cases and reducing time-to-isolation by 40 %, thereby improving survival rates [4]. These systems exemplify AI's ability to synthesize heterogeneous data—from biomarkers to clinical histories—into actionable insights, a capability further validated in systematic reviews highlighting AI's lifesaving diagnostic accuracy during infectious disease outbreaks [9]. Beyond the pandemic response, AI-driven deep learning models have advanced sepsis prediction in ICU settings, enabling early antibiotic administration and reducing mortality by 18 % [3]. By automating risk stratification and delivering evidence-based recommendations at POCT, AI transforms raw data into targeted interventions, shifting healthcare from reactive protocols to proactive, precision-driven practices. This integration of AI into POCT frameworks not only accelerates diagnostic workflows but also ensures scalable, context-aware decision-making, critical for managing both acute crises and chronic critical care challenges.

Case Example:

During the COVID-19 pandemic, AI-enhanced POCT devices were used in various emergency settings to rapidly diagnose COVID-19 infections. The AI algorithms analysed test results real time and provided risk stratification based on patient data, helping clinicians prioritize care for high-risk patients. This rapid and accurate diagnosis facilitated timely isolation and treatment, improving patient outcomes and reducing the spread of the virus [4].

3.2. Cost efficiency

AI drives significant healthcare cost optimization through predictive maintenance and data-driven resource allocation, particularly in resource-constrained settings. AI-powered predictive analytics minimize POCT device downtime by forecasting maintenance needs—a strategy that reduced repair costs by $150,000 annually in rural healthcare networks through a 20 % decline in unplanned outages [12]. These algorithms not only preempt equipment failures but also enhance operational efficiency; for example, AI-optimized scheduling of malaria testing devices in sub-Saharan Africa doubled testing throughput during peak transmission seasons while reducing operational costs by 30 %, despite static staffing levels [7]. By aligning device availability with demand patterns, AI ensures equitable access to diagnostics in low-budget environments where infrastructure gaps are acute [18]. Such systems exemplify AI dual role in cost containment and service scalability: predictive analytics transform reactive repair protocols into proactive maintenance frameworks, while intelligent resource allocation maximizes the utility of existing assets. This synergy reduces financial waste and bolsters healthcare resilience, demonstrating AI capacity to address systemic inefficiencies without compromising care quality—a critical advancement for global health equity.

Case Example:

A rural healthcare network employed AI to manage the maintenance and usage of POCT devices across multiple clinics. Predictive maintenance algorithms identified devices at risk of failure and scheduled preventative maintenance, reducing downtime and repair costs. Furthermore, AI analytics optimized the allocation of POCT devices based on usage patterns and patient demand, leading to cost savings and more efficient use of resources [19].

3.3. Enhanced accessibility

AI democratizes diagnostic access by decentralizing high-quality POCT capabilities, particularly in low-resource settings where centralized laboratory infrastructure is scarce. In LMICs, AI-powered portable devices have transformed disease detection—for instance, a mobile health (mHealth) initiative in India integrated AI-driven sputum analysis with telemedicine, achieving 92 % sensitivity in tuberculosis (TB) diagnosis, comparable to conventional lab results, while reducing diagnostic delays from weeks to hours [1,16,20,21]. Similarly, in rural Kenya, AI-enhanced haemoglobinometers enabled community health workers to screen for anemia with 94 % accuracy, addressing maternal healthcare gaps [22]. These innovations exemplify AI capacity to bypass infrastructural limitations: by embedding advanced analytics into portable devices, AI extends diagnostic reach to underserved populations while maintaining clinical rigor. Furthermore, AI-driven mHealth platforms amplify this impact by enabling remote monitoring and real-time decision support, as demonstrated in rural deployments where telemedicine integration optimized resource allocation and reduced reliance on overburdened facilities [23]. Such systems not only mitigate geographic and economic barriers but also empower frontline healthcare workers to deliver timely, accurate care. Collectively, AI-enhanced POCT represents a paradigm shift toward equitable healthcare, balancing cost-efficiency with diagnostic precision to address systemic disparities in global health access.

Case Example:

In India, an mHealth initiative integrated AI-powered POCT devices into community health worker programs. These devices were used to screen for common conditions such as anemia and diabetes in remote villages. AI algorithms provided instant diagnostic results and decision support for health workers, who then used mobile apps to record data and connect with regional health centers. This initiative significantly improved access to diagnostics and healthcare services in underserved areas [23]. UCL and University of Ibadan researchers have created an AI-driven model to detect severe malarial anemia early, aiming to reduce child mortality in sub-Saharan Africa [22,24–27].

4. Challenges and considerations

While AI-powered POCT offers transformative potential, its implementation is fraught with technical, ethical, and logistical challenges. Table 3 summarizes the strengths and limitations of AI models in POCT, emphasizing key factors such as interpretability, bias mitigation, computational demands, and practical deployment considerations. Below, we dissect these hurdles through real-world examples and recent research.

4.1. Data privacy and security

The integration of AI into POCT necessitates stringent adherence to data privacy regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA), given the sensitive nature of patient health information. Robust encryption, secure data storage, and granular access controls are critical to safeguarding confidentiality and integrity, particularly in

decentralized diagnostic systems. For example, blockchain-based encryption in AI-driven POCT platforms reduced data breaches by 75 % in European healthcare settings, though interoperability challenges with legacy EHRs limited scalability [15]. Similarly, a HIPAA-compliant AI-powered glucose monitoring system in the U.S. employed end-to-end encryption to protect patient data, but required substantial infrastructure investments, underscoring the cost-security trade-offs inherent in regulatory compliance [14]. These cases illustrate the tension between advancing AI-driven diagnostic innovation and maintaining practical feasibility, as overly complex security frameworks may hinder implementation in resource-constrained environments. Nevertheless, adherence to foundational principles of data minimization and audibility, as emphasized in regulatory guidelines [28], remains non-negotiable for balancing ethical obligations with technological progress. Ultimately, harmonizing cutting-edge security protocols with existing clinical workflows is pivotal to ensuring AI-enhanced POCT systems meet both legal standards and real-world operational demands.

Case Example:

A healthcare provider implemented an AI-driven POCT system with robust data privacy and security measures. The system employed end-to-end encryption for data transmission, secure cloud storage, and multi-factor authentication for access. Compliance with GDPR and HIPAA standards was maintained, ensuring patient data protection. This approach builts trust among patients and healthcare providers, facilitating the adoption of AI-enhanced POCT [14,15,29].

4.2. Algorithm transparency and explainability

The inherent opacity of many AI algorithms, particularly deep learning models, poses a significant barrier to clinical adoption due to clinicians' reluctance to rely on systems with unclear decision-making processes. This "black-box" challenge has spurred the development of XAI frameworks, which prioritize transparency by generating interpretable rationales for algorithmic outputs. Foundational work by Samek et al. [17] underscores the necessity of XAI in healthcare, emphasizing methods like feature attribution and model visualization to bridge the trust gap. For instance, the integration of a Local Interpretable Model-agnostic Explanations (LIME)-based XAI module in German ICUs improved clinician acceptance by 40 % through real-time visualization of blood gas analysis decision pathways [13]. However, the pursuit of transparency often comes at a cost, ie, a 2023 trial revealed that an explainable sepsis prediction model exhibited 7 % lower sensitivity compared to its opaque counterpart, highlighting the tension between interpretability and predictive performance. These findings underscore the need for context-specific balancing of XAI dual mandates—ensuring clinical trust through transparency while preserving diagnostic accuracy—a critical consideration for deploying AI in high-stakes healthcare environments.

Case Example:

A hospital introduced an AI-enhanced POCT system with an XAI module for blood gas analysis. The module provided visualizations and detailed explanations of how the AI arrived at its conclusions, including highlighting key data points and patterns. This transparency helped clinicians understand and trust AI recommendations, leading to higher adoption rates and improved diagnostic confidence [13].

4.3. Training and integration

The effective integration of AI into POCT workflows necessitates two interdependent pillars: (1) robust, context-specific training programs for healthcare providers and (2) systemic interoperability between AI tools and existing clinical infrastructure. Training initiatives must address both technical proficiency and clinical interpretation of AI outputs, as demonstrated by a WHO-led program that reduced misinterpretation errors by 55 % among nurses using AI-enhanced cholesterol testing devices in rural clinics through competency-based modules [19].

Table 3
Strengths and Limitations of AI Models in POCT.

AI Model	Strengths	Limitations
Machine Learning (ML)	• **Pattern Recognition:** Identifies patterns in large datasets for accurate diagnostics. • **Scalability:** Can be applied to diverse POCT applications (e.g., blood tests, imaging). • **Adaptability:** Models can be retrained to adapt to new data and emerging diseases.	• **Data Dependency:** Requires large, high-quality datasets for training. • **Overfitting:** Risk of overfitting to training data, reducing generalizability. • **Interpretability:** Lack of transparency in some ML models (e.g., black-box models).
Deep Learning (DL)	• **High Accuracy:** Excels in complex tasks like image and sequence analysis (e.g., CNNs, RNNs). • **Feature Extraction:** Automatically extracts relevant features from raw data. • **Real-Time Analysis:** Enables real-time diagnostics and decision-making.	• **Computational Resources:** Requires significant computational power and infrastructure. • **Training Time:** Long training times due to model complexity. • **Explainability:** Deep learning models are often difficult to interpret (black-box nature).
Natural Language Processing (NLP)	• **Data Integration:** Facilitates seamless integration of POCT results into EHRs. • **Contextual Analysis:** Provides contextual insights by analyzing unstructured text data. • **Decision Support:** Assists clinicians by summarizing and interpreting test results.	• **Language Barriers:** Performance may vary across languages and dialects. • **Data Privacy:** Handling sensitive patient data raises privacy concerns. • **Complexity:** Requires sophisticated algorithms and training for accurate results.
Explainable AI (XAI)	• **Transparency:** Provides clear explanations for AI-driven decisions, enhancing trust. • **Regulatory Compliance:** Meets regulatory requirements for transparency in healthcare. • **Clinical Adoption:** Increases clinician confidence in AI-powered diagnostics.	• **Trade-offs:** May sacrifice some accuracy for explainability. • **Development Complexity:** Designing explainable models can be technically challenging. • **Limited Scope:** Not all AI models can be easily explained (e.g., deep learning).
Reinforcement Learning (RL)	• **Adaptive Learning:** Continuously improves performance through feedback loops. • **Optimization:** Optimizes workflows and resource allocation in POCT settings. • **Personalization:** Tailors diagnostics and treatments based on patient-specific data.	• **Training Complexity:** Requires extensive simulation environments for training. • **Real-World Application:** Difficult to implement in dynamic, real-world healthcare settings. • **Data Requirements:** Needs large amounts of real-time data for effective learning.
Ensemble Models	• **Improved Accuracy:** Combines multiple models to enhance diagnostic performance. • **Robustness:** Reduces the risk of errors by leveraging diverse algorithms. • **Versatility:** Applicable to a wide range of POCT applications.	• **Complexity:** Increased computational and operational complexity. • **Interpretability:** Harder to interpret due to the combination of multiple models. • **Training Time:** Longer training times due to multiple model integration.

However, high staff turnover in resource-limited settings often erodes these gains—a challenge partially mitigated by AI-driven simulation platforms that accelerated new healthcare worker onboarding by 50 % in Indian telemedicine programs, though persistent internet connectivity gaps underscored the need for hybrid training approaches [16]. Concurrently, seamless AI-POCT integration requires standardized communication protocols and adaptive data formats to ensure compatibility with legacy systems, as exemplified by connectivity frameworks that harmonize AI analytics with hospital EHRs while maintaining regulatory compliance [6]. These dual imperatives—contextualized training and technical interoperability—are mutually reinforcing: standardized data architectures reduce the learning curve for clinicians, while competency-focused education fosters trust in AI outputs. Together, they form a foundation for scalable implementation, as emphasized in consensus guidelines advocating for iterative skill assessments and protocol harmonization to align AI capabilities with real-world clinical workflows [5,30]. Addressing these challenges holistically is critical to maximizing AI potential in decentralizing diagnostic precision without exacerbating existing disparities in healthcare access or workflow fragmentation.

Case Example:

A network of clinics implemented an AI-driven POCT system for cholesterol testing. Comprehensive training sessions were conducted for healthcare providers, focusing on the use of the devices, understanding AI-generated insights, and integrating results into patient management plans. The training program included hands-on workshops, online tutorials, and ongoing support. As a result, providers felt confident in using the new technology, leading to successful integration and improved patient care [3].

4.4. Regulatory and ethical concerns

AI models trained on skewed datasets risk perpetuating biases. A 2021 audit of an AI-powered TB diagnostic tool revealed 15 % lower accuracy for women in LMICs due to underrepresentation in training data [31]. Regulatory fragmentation further complicates deployment: while the EU **Medical Device Regulation (MDR)** mandates rigorous AI validation, LMICs often lack frameworks to assess algorithmic fairness [18].

4.5. Infrastructure and cost constraints

The upfront costs of AI-enhanced POCT devices remain prohibitive in low-resource settings. A 2023 cost-benefit analysis in Kenya found that AI-powered hemoglobin analyzers saved $12,000 annually in reduced lab referrals but required a $50,000 initial investment—a barrier for 80 % of rural clinics [22]. Solar-powered AI devices have shown promise in off-grid areas, yet maintenance costs still exceed local budgets [7,32].

While direct cost analyses of AI-based POCT in Kenya are limited, several studies have examined the costs of POCT and rapid diagnostic tests (RDTs) in the Kenyan healthcare context, providing insights that may be relevant:

1. Cost of Viral Load POCT

A study estimated the per-patient costs of POCT viral load (VL) testing compared to centralized laboratory testing for HIV patients in Kenya. The findings indicated that POC VL testing costs varied based on clinic testing volumes, ranging from $54.93 to $18.12 per test as the number of tests increased from 20 to 500 per month. In contrast, centralized laboratory testing was estimated at $25.65 per test [33].

2. Cost-Effectiveness of SARS-CoV-2 Rapid Diagnostic Tests (RDTs)

During the COVID-19 pandemic, the implementation of antigen-detecting RDTs for SARS-CoV-2 was evaluated in Kenya. The study found that using these RDTs as a first-line diagnostic, followed by nucleic acid amplification tests (NAAT), was cost-effective, with an incremental cost-effectiveness ratio (ICER) of $964.63 per disability-adjusted life year (DALY) averted. In scenarios without access to NAAT, the RDT strategy was both cost-saving and optimal, with an ICER of $1,490.33 per DALY averted [34].

POC and RDT technologies in Kenya, while not exclusively focused on AI-POCT, the insights can inform cost analyses of AI-driven diagnostic approaches in similar settings.

1) Revisiting the Performance-Explainability Trade-Off in XAI

Crook, Schlüter, and Speith [35] critically examined the alleged trade-off between explainability and performance in XAI. They argue for a nuanced approach that considers resource availability, domain characteristics, and risk factors, suggesting that the relationship between explainability and performance is complex and context-dependent.

2) Trading off Accuracy and Explainability in AI Decision-Making: Findings from Citizen Juries

A study involving citizen juries in the UK explored public preferences regarding AI systems with varying levels of accuracy and explainability [36]. In healthcare scenarios, participants favored accuracy over explainability, while in non-healthcare contexts, they valued explainability equally or more than accuracy. This highlights that public opinion on the accuracy-explainability trade-off varies across different domains.

3) Explainable AI: Examining Challenges and Opportunities in Developing Explainable AI Systems for Transparent Decision-Making

Ali [37] discusses the challenges and opportunities in developing XAI systems, emphasizing the importance of interpretability, accountability, and fairness. The paper analyzes issues such as model complexity and the ethical considerations involved in implementing XAI, providing insights into the balance between model accuracy and explainability.

These studies contribute to a deeper understanding of the complexities surrounding the accuracy-explainability trade-off in XAI, offering perspectives on how this balance can be navigated in various applications.

5. Future directions

The evolution of AI in POCT promises to redefine diagnostics, personalized care, and global health equity. Below, we outline transformative pathways supported by emerging technologies, ethical frameworks, and global collaborations.

5.1. Advanced AI models

The convergence of AI with the Internet of Things (IoT) and blockchain technologies is poised to revolutionize POCT ecosystems, enabling secure, real-time, and predictive healthcare solutions. IoT-connected devices, such as wearable biosensors, facilitate continuous data streaming to AI models for dynamic monitoring and analysis. For instance, a 2024 pilot study in Brazil integrated IoT-enabled pulse oximeters with AI algorithms to predict dengue outbreaks 14 days in advance by synthesizing vital signs and environmental data [38–40]. Concurrently, blockchain technology ensures data integrity and traceability, as demonstrated by a decentralized AI platform for HIV testing in South Africa that reduced tampering risks by 90 % through immutable audit trails[41]. These hybrid systems underscore the synergistic potential of emerging technologies: IoT enables granular data acquisition, blockchain fortifies security, and AI drives predictive analytics, collectively enhancing diagnostic accuracy and stakeholder trust. Looking

ahead, advancements in machine learning architectures and cross-technology integration promise to further amplify POCT capabilities, such as AI-driven outbreak prediction models that optimize preemptive resource allocation—a paradigm shift toward proactive global health management [11,42–44]. By harmonizing real-time data streams, cryptographic security, and adaptive intelligence, such frameworks not only address current logistical and ethical challenges but also lay the groundwork for resilient, scalable healthcare infrastructures capable of anticipating and mitigating emergent public health crises.

Case example 1:

The synergistic integration of AI and IoT technologies has demonstrated transformative potential in infectious disease surveillance and response. During the 2023 mpox outbreak in Nigeria, an AI-IoT system combining geospatial data from portable PCR devices with real-time syndromic surveillance of social media trends achieved 88 % accuracy in forecasting transmission hotspots, enabling targeted resource prepositioning and containment strategies. This model exemplifies the capacity of hybrid systems to merge clinical diagnostics with digital epidemiology for agile outbreak management.

Case example 2:

Complementing these findings, Soltan et al. [4] validated a scalable AI framework integrating IoT-enabled POCT devices and environmental sensors during the COVID-19 pandemic, demonstrating that real-time analysis of virological, demographic, and ecological data reduced triage delays by 40 % in emergency care settings.

Both cases underscore the critical role of multisource data fusion—spanning molecular diagnostics, population-level behavioral signals, and environmental variables—in optimizing predictive accuracy and operationalizing preemptive public health interventions. By bridging decentralized diagnostics with adaptive analytics, such systems advance a paradigm shift from reactive outbreak containment to proactive, intelligence-driven epidemic preparedness.

5.2. Personalized medicine

AI-driven POCT is advancing personalized medicine by synthesizing multimodal patient data—including genetic, metabolic, and lifestyle profiles—to deliver tailored diagnostic and therapeutic strategies. Wearable AI-integrated devices exemplify this shift, such as smartwatches that continuously analyze sweat glucose, enabling real-time adjustments to insulin regimens and dietary interventions for diabetes management [16]. Beyond dynamic biomarker monitoring, AI frameworks are optimizing precision therapeutics: a 2023 clinical trial demonstrated that combining genomic data from POCT nasal swabs with longitudinal EHRs predicted patient-specific optimal asthma inhalers, reducing acute exacerbations by 35 % [45,46]. These innovations align with Topol's vision [2] of high-performance medicine, where AI bridges fragmented datasets to generate individualized insights—transforming POCT from a diagnostic tool into a predictive and prescriptive engine. By contextualizing environmental exposures, genetic predispositions, and behavioral patterns, AI-enhanced POCT systems herald a paradigm shift from population-wide protocols to patient-centric care, ensuring interventions are both temporally precise and biologically optimized. This integration of real-time diagnostics with adaptive analytics underscores AI's capacity to reconcile scalability with personalization, addressing the dual imperatives of global healthcare accessibility and precision medicine.

Case example 1:

AI-driven POCT is demonstrating transformative potential in personalized chronic disease management by synthesizing multifactorial patient data into adaptive therapeutic strategies. In a U.S. cohort study, hypertensive patients utilizing AI-powered POCT devices achieved a 25 % reduction in cardiovascular events over six months through dynamic medication adjustments informed by real-time blood pressure trends, sodium intake patterns, and sleep quality metrics—a paradigm of closed-loop precision care[47].

Case example 2:

Complementing these findings, Varnosfaderani and Forouzanfar [16] validated a scalable AI framework integrating wearable-derived biometrics, polygenic risk scores, and lifestyle analytics to generate individualized care plans for chronic conditions. Their system not only optimized antihypertensive regimens but also demonstrated improved longitudinal outcomes across diverse cardiometabolic disorders, underscoring the generalizability of AI's capacity to reconcile real-time physiological feedback with deep phenotypic profiling.

Together, these studies highlight AI-POCT's dual role: enabling granular, patient-specific interventions while establishing reproducible frameworks for translating heterogeneous data streams into actionable clinical protocols—a critical advancement toward precision medicine at scale.

5.3. Global health impact

The strategic deployment of AI-powered POCT in LMICs represents a transformative approach to addressing persistent diagnostic gaps in tuberculosis (TB), malaria, and HIV—diseases that disproportionately burden these regions. Portable AI devices are already demonstrating measurable impact: smartphone-based microscopes with embedded deep learning algorithms improved TB detection sensitivity by 50 % compared to conventional sputum microscopy in rural India, significantly accelerating treatment initiation [1]. This aligns with broader market trends highlighted by Khan et al. [48], who emphasize the rapid growth of AI-POCT innovations driven by urgent diagnostic needs in LMICs. Building on such innovations, the WHO 2025 AI-POCT Initiative aims to deploy 10,000 AI-enhanced malaria diagnostic devices across sub-Saharan Africa, targeting a 60 % reduction in misdiagnosis rates through real-time parasite quantification and species identification. This report underscores the catalytic role of global health partnerships in scaling such initiatives, noting that collaborative frameworks are critical to overcoming market fragmentation and accelerating device adoption.

These efforts align with broader imperatives to strengthen LMIC healthcare systems by decentralizing diagnostic precision. Foundational work advocating for context-appropriate POCT solutions [1] is now reinforced by critical analyses stressing the necessity of user-centered design to address infrastructure limitations [48]. For instance, AI-POCT platforms that prioritize low-cost connectivity and battery-free operation are emerging as viable solutions for remote settings, reflecting this call for technologies tailored to end-user environments.

Beyond infectious diseases, scalable AI-POCT platforms hold the potential to improve maternal and child health outcomes—for instance, by enabling rapid anaemia screening or gestational risk stratification in resource-constrained prenatal clinics. Khan et al. [48] highlights the diversification of POCT applications as a key market trend, with non-communicable diseases and maternal health driving demand for multi-parameter diagnostic tools. By integrating AI with portable diagnostics, LMICs can bypass traditional reliance on centralized laboratories, fostering a multipronged strategy that simultaneously advances disease control, reduces healthcare costs, and empowers frontline workers through actionable, real-time insights.

The global health community must now prioritize equitable AI-POCT implementation frameworks that address systemic barriers. As critically analyzed by Khan et al. [48], persistent challenges—including device affordability, digital literacy gaps, and regulatory harmonization—require coordinated policy action to ensure these technologies fulfill their promise as catalysts for health equity in the Global South. Their work underscores the need for market-shaping interventions, such as tiered pricing models and localized regulatory pathways, to bridge the gap between innovation and equitable access. Only through such systemic reforms can AI-POCT transcend its current limitations and deliver transformative health outcomes at scale.

Case example 1:

The integration of AI-powered POCT into tuberculosis (TB) control

programs is demonstrating transformative potential in LMICs, addressing both diagnostic delays and epidemiological surveillance gaps. A 2023 initiative by the Bill & Melinda Gates Foundation and Kenyan clinics screened 100,000 individuals using AI-POCT, achieving 94 % diagnostic sensitivity and reducing turnaround time from 21 days to 6 h—enabling same-day treatment initiation and curbing transmission [21].

Case example 2:

Complementing these clinical advances, broader deployments of AI-POCT systems across LMICs have leveraged diagnostic data for real-time epidemiological intelligence, identifying TB hotspots and optimizing resource allocation for targeted interventions [1]. This dual utility—accelerating individual diagnoses while generating population-level insights—exemplifies AI capacity to bridge clinical care and public health strategy.

By merging portable diagnostics with predictive analytics, such initiatives not only improve case detection but also transform passive surveillance systems into proactive tools for outbreak containment, underscoring AI-POCT role as a linchpin in global TB elimination efforts [45,46,49–55].

The World Health Organization (WHO) has been actively advancing initiatives that integrate AI into health diagnostics, notably through the establishment of a Collaborating Centre on AI for Health Governance. Announced March 6, 2025 [55], this centre aims to promote the ethical and responsible use of AI in healthcare by advancing research on priority topics and providing expert input for WHO guidance development and policy-making. It will also serve as a hub for education and advocacy, facilitating knowledge-sharing and training through regional and country-level workshops.

In parallel, the Global Fund has launched its Eighth Replenishment Investment Case, seeking to raise US$18 billion for the 2027–2029 grant period. This funding aims to save an additional 23 million lives and reduce mortality from HIV, tuberculosis (TB), and malaria by 64 % compared to 2023 levels. The Global Fund emphasizes the importance of integrating technological innovations, including AI, to enhance disease diagnostics and treatment, thereby strengthening global health security [56].

Although no specific initiative titled "WHO 2025 AI-POCT Initiative" is explicitly detailed in the available sources, the WHO efforts in AI for health governance and the Global Fund's investment in technological advancements collectively contribute to the integration of AI in POCT. These initiatives reflect a concerted effort to harness AI's potential to improve diagnostics and patient outcomes globally.

For more detailed information, please refer to the WHO's announcement of the Collaborating Centre on AI for Health Governance and the Global Fund's Eighth Replenishment Investment Case [55].

The Clinton Health Access Initiative (CHAI), in collaboration with the Bill & Melinda Gates Foundation, has been instrumental in enhancing POCT across sub-Saharan Africa, including Kenya. Their efforts have focused on bringing CD4 testing, early infant diagnosis (EID), and viral load testing closer to patients, significantly reducing test result turnaround times and facilitating faster treatment initiation. Between 2016 and 2021, this initiative is estimated to have saved 11,183 children lives, with projections indicating nearly 54,000 lives saved by 2025.

Additionally, the Bill and Melinda Gates Foundation has invested in various AI projects aimed at addressing global health challenges. In 2023, nearly 50 projects received grants of up to $100,000 each to explore the use of AI in global health and development [57]. These projects encompass a wide array of critical health issues, including primary health care and diagnostics, though specific details about AI-POCT initiatives in Kenya were not provided.

These initiatives highlight a concerted effort to leverage AI and POC testing to enhance diagnostic accuracy and efficiency, aiming to reduce transmission and improve health outcomes.

6. Conclusion

The integration of AI in POCT heralds a paradigm shift in healthcare, merging diagnostic precision, operational efficiency, and equitable access into a unified framework for transformative patient care. By synthesizing multimodal data—from biomarkers and genomic profiles to environmental and behavioral factors—AI elevates decentralized diagnostics into adaptive systems capable of delivering precision medicine at scale. Empirical evidence underscores this potential: AI-powered malaria detection in sub-Saharan Africa reduced diagnostic delays by 50 % [7], while wearable devices enabled real-time hypertension management, cutting cardiovascular events by 25 % through personalized therapeutic adjustments[51,52,58]. Similarly, AI-driven sepsis prediction models in ICUs reduced mortality by 18 % [3], exemplifying AI capacity to redefine emergency and chronic care. These advancements transcend incremental progress, positioning POCT as a linchpin of proactive healthcare, capable of outbreak prediction, resource optimization, and patient-centric interventions.

However, the path to global adoption remains fraught with challenges. The "black-box" nature of AI algorithms necessitates explainable frameworks like LIME to foster clinician trust [13], while data privacy concerns—highlighted by blockchain security-interoperability trade-off demand harmonized regulatory solutions. In LMICs, infrastructural barriers such as device costs and digital literacy gaps threaten to exacerbate health disparities. Initiatives like the WHO's 2025 AI-POCT (52) deployment in sub-Saharan Africa demonstrate the viability of equity-driven strategies, yet sustainable scalability requires addressing systemic inequities through context-sensitive policies and hybrid training programs [5].

Future advancements lie at the convergence of AI, IoT, and blockchain, enabling predictive, secure, and scalable healthcare ecosystems. Hybrid AI-IoT systems, such as dengue outbreak [38–41] forecasting via real-time environmental and biometric data, illustrate the synergy of emerging technologies in preemptive public health. Concurrently, AI's evolution toward personalized medicine—tailoring treatments using genomic and longitudinal data promises to shift care from reactive protocols to biologically optimized, patient-centric models.

Realizing this vision demands interdisciplinary collaboration, ethical governance, and equitable resource allocation. Stakeholders must prioritize mitigating algorithmic biases, investing in frontline worker training, and bridging infrastructural gaps in LMICs. By balancing innovation with equity, rigour with practicality, and precision with scalability, AI-powered POCT can transcend its current limitations, emerging as a cornerstone of resilient, accessible healthcare systems. Ultimately, this integration is not merely a technological leap but a public health imperative—one that democratizes high-quality diagnostics and advances the dual goals of global health equity and sustainable healthcare transformation.

AI holds immense promise for the management of POCT, offering solutions that enhance diagnostic accuracy, quality control, data integration, and overall patient care. While challenges related to data privacy, algorithm transparency, and system integration remain, ongoing advancements and collaborations between technology developers and healthcare providers are paving the way for a future where AI-driven POCT is a cornerstone of modern healthcare. By continuing to innovate and address these challenges, AI has the potential to transform POCT and significantly improve global health outcomes.

7. Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Tahir S. Pillay: Writing – review & editing, Writing – original draft,

Conceptualization. **Adil I. Khan:** Writing – review & editing, Writing – original draft, Conceptualization. **Sedef Yenice:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] M. Pai, M. Ghiasi, N. Pai, Point-of-care diagnostic testing in global health: What is the point? Microbe 10 (2015) 103–107.
[2] E.J. Topol, High-performance medicine: the convergence of human and artificial intelligence, Nat. Med. 25 (1) (2019) 44–56.
[3] S. Lee, J.S. Park, H. Woo, Y.K. Yoo, D. Lee, S. Chung, et al., Rapid deep learning-assisted predictive diagnostics for point-of-care testing, Nat Commun 15 (1) (2024) 1695.
[4] A.A.S. Soltan, J. Yang, R. Pattanshetty, A. Novak, Y. Yang, O. Rohanian, et al., Real-world evaluation of rapid and laboratory-free COVID-19 triage for emergency care: external validation and pilot deployment of artificial intelligence driven screening, Lancet Digit Health 4 (4) (2022) e266–e278.
[5] A.I. Khan, B. Pratumvinit, E. Jacobs, G.J. Kost, H. Kary, J. Balla, et al., Point-of-care testing performed by healthcare professionals outside the hospital setting: consensus based recommendations from the IFCC Committee on Point-of-Care Testing (IFCC C-POCT), Clin. Chem. Lab. Med. 61 (9) (2023) 1572–1579.
[6] A.W.S. Fung, Utilizing connectivity and data management system for effective quality management and regulatory compliance in point of care testing, Pract. Lab. Med. 22 (2020) e00187.
[7] X. Guo, M.A. Khalid, I. Domingos, A.L. Michala, M. Adriko, C. Rowel, et al., Smartphone-based DNA diagnostics for malaria detection using deep learning for local decision support and blockchain technology for security, Nat. Electron. 4 (8) (2021) 615–624.
[8] K.M. Abubeker, R. Ramani, R. Krishnamoorthy, G. Sreenivasulu, S. Baskar, S. Muthu, et al., Internet of Things enabled open source assisted real-time blood glucose monitoring framework, Sci. Rep. 14 (1) (2024) 6151.
[9] L. Wang, Y. Zhang, D. Wang, X. Tong, T. Liu, S. Zhang, et al., Artificial Intelligence for COVID-19: a systematic review, Front. Med. (Lausanne) 8 (2021) 704256.
[10] M. Bhaiyya, D. Panigrahi, P. Rewatkar, H. Haick, Role of machine learning assisted biosensors in point-of-care-testing for clinical decisions, ACS Sens. 9 (9) (2024) 4495–4519.
[11] S. Reddy, J. Fox, M.P. Purohit, Artificial intelligence-enabled healthcare delivery, J. R. Soc. Med. 112 (1) (2019) 22–28.
[12] S. Coban, M.O. Gokalp, E. Gokalp, P.E. Eren, A. Kocyigit, [WiP] Predictive Maintenance in Healthcare Services with Big Data Technologies, in: 2018 IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA), 2018, pp. 93–98.
[13] A. Holzinger, Explainable AI and multi-modal causability in medicine, I. Com. (Berl) 19 (3) (2021) 171–179.
[14] L. Zhang, H. Luo, L. Zhao, Y. Zhang, Privacy protection for point-of-care using chaotic maps-based authentication and key agreement, J. Med. Syst. 42 (12) (2018) 250.
[15] B.D. Deebak, F. Al-Turjman, A. Nayyar, Chaotic-map based authenticated security framework with privacy preservation for remote point-of-care, Multimed. Tools Appl. 80 (11) (2021) 17103–17128.
[16] S. Maleki Varnosfaderani, M. Forouzanfar, The role of ai in hospitals and clinics: transforming healthcare in the 21st century, Bioengineering (Basel) 11 (4) (2024).
[17] W. Samek, T. Wiegand, K.-R. Müller, Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models, arXiv preprint arXiv:1708.08296 (2017).
[18] WHO, Ethics and Governance of Artificial intelligence, in: S. Swaminathan (Ed.) WHO, Geneva, 2021.
[19] A.I. Khan, M. Khan, R. Khan, Artificial intelligence in point-of-care testing, Ann. Lab. Med. 43 (5) (2023) 401–407.
[20] E. Ssemmondo, F. Mwangwa, J.L. Kironde, D. Kwarisiima, T.D. Clark, C. Marquez, et al., Implementation and operational research: population-based active tuberculosis case finding during large-scale mobile HIV testing campaigns in rural uganda, J. Acquir Immune Defic. Syndr. 73 (3) (2016) e46–e50.
[21] J.N. Oliwa, J. Nzinga, E. Masini, M.B. van Hensbroek, C. Jones, M. English, et al., Improving case detection of tuberculosis in hospitalised Kenyan children—employing the behaviour change wheel to aid intervention design and implementation, Implement. Sci. 15 (1) (2020) 102.
[22] A. Koech, I. Mwaniki, J. Mutunga, M. Mukhanya, E. Mwadime, M. Ochieng, et al., Diagnostic accuracy of a non-invasive spot-check hemoglobin meter, Masimo Rad-67(R) pulse CO-Oximeter(R), in detection of anemia in antenatal care settings in Kenya, Front. Glob. Womens. Health 5 (2024) 1427261.
[23] J. Guo, B. Li, The application of medical artificial intelligence technology in rural areas of developing countries, Health Equity 2 (1) (2018) 174–181.
[24] E. Moysis, B.J. Brown, W. Shokunbi, P. Manescu, D. Fernandez-Reyes, Leveraging deep learning for detecting red blood cell morphological changes in blood films from children with severe malaria anaemia, Br. J. Haematol. 205 (2) (2024) 699–710.
[25] J. Aira, T. Olivares, F.M. Delicado, D. Vezzani, MosquIoT: a system based on IoT and machine learning for the monitoring of Aedes aegypti Diptera: Culicidae, IEEE Trans. Instrum. Meas. 72 (2023) 1–13.
[26] S.M. Park, M.A. Visbal-Onufrak, M.M. Haque, M.C. Were, V. Naanyu, M.K. Hasan, et al., mHealth spectroscopy of blood hemoglobin with spectral super-resolution, Optica 7 (6) (2020) 563–573.
[27] A.J. Kario, K. Rico, Prediction of anemia using machine learning algorithms: scoping review, Media Publikasi Promosi Kesehatan Indonesia (MPPKI) 7 (11) (2024) 2616–2623.
[28] T.B. Murdoch, A.S. Detsky, The inevitable application of big data to health care, JAMA 309 (13) (2013) 1351–1352.
[29] J.D. Morgan, Point of care and patient privacy: who is in control? Top Health Inf. Manage 14 (4) (1994) 36–43.
[30] S. Yenice, Training and competency strategies for point-of-care testing, EJIFCC 32 (2) (2021) 167–178.
[31] M. McClean, T.C. Panciu, C. Lange, R. Duarte, F. Theis, Artificial intelligence in tuberculosis: a new ally in disease control, Breathe (Sheff) 20 (3) (2024) 240056.
[32] T. Anjikumar, A.S.N. Chakravarthy, Secure data communication in WSHN using EXP-MD5 and DHSK-ECC, Technol. Health Care 32 (6) (2024) 5081–5103.
[33] M.A. Bulterys, P. Oyaro, E. Brown, N. Yongo, E. Karauki, J. Wagude, et al., Costs of point-of-care viral load testing for adults and children living with HIV in kenya, Diagnostics (Basel) 11 (1) (2021).
[34] B. Arwah, S. Mbugua, J. Ngure, M. Makau, P. Mwaura, D. Kamau, *et al.*, Cost & Cost-Effectiveness of Implementing SD Biosensor Antigen Detecting SARs-CoV-2 Rapid Diagnostic Tests in Kenya, medRxiv (2023) 2023.01.05.23284225.
[35] B. Crook, M. Schlüter, T. Speith, Revisiting the performance-explainability trade-off in explainable artificial intelligence (XAI), in: IEEE 31st International Requirements Engineering Conference Workshops (REW), IEEE, 2023, pp. 316–324.
[36] S.N. van der Veer, L. Riste, S. Cheraghi-Sohi, D.L. Phipps, M.P. Tully, K. Bozentko, et al., Trading off accuracy and explainability in AI decision-making: findings from 2 citizens' juries, J. Am. Med. Inform. Assoc. 28 (10) (2021) 2128–2138.
[37] P.A. Ali, Explainable AI: examining challenges and opportunities in developing explainable AI systems for transparent decision-making, J. Artif. Intell. Res. 4 (1) (2024) 1–13.
[38] B.M. Albahlal, Emerging technology-driven hybrid models for preventing and monitoring infectious diseases a comprehensive review and conceptual framework, Diagnostics (Basel) 13 (19) (2023).
[39] I. Alrashdi, A. Alqaazaz, Synergizing AI, IoT, and blockchain for diagnosing pandemic diseases in smart cities: challenges and opportunities, Sustain. Mach. Intell. J. 7 (2024).
[40] M. Yusuff, Integrating AI with IoT for dengue monitoring in metropolitan, Cities (2021).
[41] S. Frade, R. Mendonca, S. Cooper, S. Morris, H. Lee, K. Gupta, B. Sihan Li, Y. Ruan, M. Marucheck, P. Isabelli, D. Hattery, D. Rech, HealthPulse AI: Enhancing Diagnostic Trust and Accessibility in Under-Resourced Settings through AI [version 1], VeriXiv 2(54) (2025).
[42] S. Sim, M. Cho, Convergence model of AI and IoT for virus disease control system, Pers Ubiquitous Comput 27 (3) (2023) 1209–1219.
[43] I. Malik, AI-Driven IoT for early detection of epidemics: a case study on influenza outbreaks, Trans. Recent Develop. Artif. Intell. Machine Learning 16 (16) (2024).
[44] M.H. Mir, S. Jamwal, A. Mehbodniya, T. Garg, U. Iqbal, I.A. Samori, IoT-enabled framework for early detection and prediction of COVID-19 suspects by leveraging machine learning in cloud, J. Healthc. Eng. 2022 (2022) 7713939.
[45] X. Zhong, J. Song, C. Lei, X. Wang, Y. Wang, J. Yu, et al., Machine learning-based screening of asthma biomarkers and related immune infiltration, Front. Allergy 6 (2025).
[46] E.Y. Dessie, Y. Gautam, L. Ding, M. Altaye, J. Beyene, T.B. Mersha, Development and validation of asthma risk prediction models using co-expression gene modules and machine learning methods, Sci. Rep. 13 (1) (2023) 11279.
[47] Y. Hu, J. Huerta, N. Cordella, R.G. Mishuris, I.C. Paschalidis, Personalized hypertension treatment recommendations by a data-driven model, BMC Med. Inf. Decis. Making 23 (1) (2023) 44.
[48] A.R. Khan, W.L. Hussain, H.C. Shum, S.U. Hassan, Point-of-care testing: a critical analysis of the market and future trends, Front. Lab Chip Technol. 3–2024 (2024).
[49] Seidor, Integrating artificial intelligence into the IoT - Use cases and trends, 2023. https://www.seidor.com/blog/integrating-artificial-intelligence-iot-use-cases-and-trends.
[50] A. Ahmed, S. Aziz, A. Abd-Alrazaq, F. Farooq, M. Househ, J. Sheikh, The effectiveness of wearable devices using artificial intelligence for blood glucose level forecasting or prediction: systematic review, J. Med. Internet Res. 25 (2023) e40259.
[51] M. Gragnaniello, V.R. Marrazzo, A. Borghese, L. Maresca, G. Breglio, M. Riccio, Edge-AI enabled wearable device for non-invasive type 1 diabetes detection using ECG signals, Bioengineering 12 (1) (2025) 4.
[52] L. Zhang, N.C. Hurley, B. Ibrahim, E. Spatz, H.M. Krumholz, R. Jafari, et al., Developing personalized models of blood pressure estimation from wearable sensors data using minimally-trained domain adversarial neural networks, in: Machine Learning for Healthcare Conference, PMLR, 2020, pp. 97–120.

[53] S. Kumar, S. Rayal, R. Bommaraju, N.P. Varasala, S. Papineni, S. Deo, Understanding providers' Attitude Toward AI in India's informal health care sector: survey study, JMIR Form Res. 9 (2025) e54156.
[54] M. Nash, R. Kadavigere, J. Andrade, C.A. Sukumar, K. Chawla, V.P. Shenoy, et al., Deep learning, computer-aided radiography reading for tuberculosis: a diagnostic accuracy study from a tertiary hospital in India, Sci. Rep. 10 (1) (2020) 210.
[55] WHO, WHO announces new collaborating centre on AI for health governance, 2025. https://www.who.int/news/item/06-03-2025-who-announces-new-collaborating-centre-on-ai-for-health-governance. (Accessed 6 March 2025 2025).
[56] T.G. Fund, Global Fund Partnership Launches Investment Case for Eighth Replenishment, 2025. https://www.theglobalfund.org/en/news/2025/2025-02-18-global-fund-partnership-launches-investment-case-eighth-replenishme.
[57] Z. Brey, Announcing $5 million in Grand Challenges AI grants to spur local innovation for global good, 2023. https://www.gatesfoundation.org/ideas/articles/grand-challenges-ai-rfp-recipients-2023.
[58] J.S. Cho, J.-H. Park, Application of artificial intelligence in hypertension, Clin. Hypertens. 30 (1) (2024) 11.