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Systematic Review

Comparative Analysis of the Diagnostic Performance of AI POCT and Traditional POCT: A Systematic Review

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Abstract

Introduction: Artificial intelligence (AI) has increasingly been integrated into point-of-care testing (POCT) systems to enhance diagnostic accuracy and overcome limitations inherent in traditional POCT methods, particularly those dependent on manual result interpretation. This systematic review compares the diagnostic performance of AI-enhanced POCT and traditional POCT across a range of medical conditions and clinical settings. **Methods:** Using PRISMA 2020 guidelines, a comprehensive search was conducted across four databases—PubMed, Google Scholar, ScienceDirect, IEEE Xplore and Semantic Scholar—covering publications from January 2015 to April 2024. Eligible studies reported at least one diagnostic accuracy metric, such as sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), or area under the curve (AUC). **Results:** Eight studies met the inclusion criteria, targeting diseases such as COVID-19, influenza, diabetic retinopathy, streptococcal pharyngitis, myocardial infarction, and β- thalassemia. Across studies, AI-enhanced POCT demonstrated comparable and superior diagnostic performance compared to traditional methods. Sensitivity and specificity of AI-driven systems typically exceeded 94%, with some models reporting AUC values approaching 0.99. In contrast, traditional POCT devices showed greater variability in performance, with sensitivities ranging from 24% to 93% depending on disease type and user interpretation. AI integration reduced subjectivity, improved consistency, and enabled automated interpretation of complex data, particularly in imaging-based diagnostics and low- resource environments. However, challenges such as infrastructure demands, algorithm bias, and regulatory gaps persist, especially in under-resourced settings. **Conclusion:** Despite these hurdles, AI-enhanced POCT offers significant potential to democratize access to expert-level diagnostics, reduce diagnostic errors, and speed up decision-making in high-pressure clinical environments. Rather than replacing traditional POCT, AI-based systems should be viewed as complementary tools that fill critical gaps where precision, standardization, and automation are essential. The findings reveal the need for further head-to-head comparative studies and broader validation across diverse populations.

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1. Introduction

Point-of-care testing (POCT) has revolutionized healthcare by providing fast diagnostic results right where patients are, whether in a doctor's office, an emergency room, or even a remote clinic. No longer confined to traditional labs, this technology helps doctors make quick decisions that can save lives or improve care [1]. It all started way back in the 1950s with simple urine dipsticks and grew in the 1970s with early glucose meters for diabetes monitoring [2]. Now, POCT is a high- tech field, using tools like lateral flow tests (think pregnancy tests), advanced molecular diagnostics, and tiny microfluidic devices that analyze samples in minutes [3].

In 1988, the Clinical Laboratory Improvement Amendments (CLIA) made it easier for non-lab staff, like nurses or paramedics, to run these tests by setting clear quality standards for simple diagnostics, opening the door to testing in all kinds of settings [4]. Today, POCT is a game-changer for catching infectious diseases early, managing chronic conditions like diabetes, and handling emergencies [5]. The global diagnostics market is expanding quickly. Recent peer-reviewed research shows the point-of-care (POC) diagnostics sector was valued at about $53 billion in 2024 and is projected to grow substantially through the early 2030s as demand for rapid, accessible health testing rises worldwide [6].

Traditional point-of-care testing (POCT), while widely used, has some notable drawbacks. One big issue is that many tests, like lateral flow assays (think rapid COVID or pregnancy tests), rely on someone visually interpreting faint lines, which can be subjective and lead to mistakes; either missing a positive result or falsely detecting one [7, 8]. For instance, during the COVID-19 pandemic, rapid antigen tests were only about 72% accurate for symptomatic cases and struggled even more when viral loads were low, raising questions about their reliability [9]. In addition, environmental factors like heat or humidity can alter test performance, especially in places like rural clinics where proper storage is not always possible [10]. These issues highlight the need for better POCT solutions that reduce human error while keeping the speed and convenience that make these tests so valuable.

Artificial intelligence (AI) is stepping up to tackle the weaknesses of traditional point-of-care testing (POCT) in a big way [11]. By combining machine learning with POCT devices, AI makes tests more accurate through things like automated image analysis and consistent result interpretation [12]. For example, smartphone apps that read lateral flow tests (like those for COVID-19) have boosted sensitivity to an impressive 98.1%, compared to 80.4% when human eyes read the results [13]. AI is also shining in other areas, like retinal imaging for diabetic eye disease, where it matches the accuracy of expert eye doctors in regular clinics [14]. Beyond infections, AI-enhanced POCT is showing potential for heart health checks, estimating gestational age, and tracking chronic conditions, with the added perk of getting smarter over time through algorithm updates and linking with digital health records [15].

While AI-powered point-of-care testing (POCT) holds huge promise, rolling it out widely is not without challenges [16]. AI cuts down on human error in test interpretation [17], but it often needs reliable internet and power, which can be a problem in remote or low-resource areas [18]. There are also worries about data privacy, biases in AI algorithms, and the need for thorough clinical testing to ensure accuracy across different populations [16]. Regulatory rules are still catching up, adding another layer of complexity [19].

This systematic review fills a key gap by directly comparing AI-enhanced POCT with traditional methods across various medical uses. By pulling together evidence from studies, it aims to clarify the strengths, weaknesses, and best applications for both approaches. The results will help doctors, policymakers, and tech developers make informed choices in areas like emergency medicine, public health screening, and healthcare investments, ultimately pushing for fairer access to diagnostics and better patient care globally.

2. Methodology

2.1. Study Design

This systematic review was carefully designed using the PRISMA 2020 guidelines to ensure its transparency, repeatability, and scientific robustness. It pulls together peer-reviewed studies and preprints to compare directly or indirectly the diagnostic accuracy of AI-powered point-of-care testing (POCT) with traditional POCT across different medical conditions based on available studies. By doing so, it offers a clear picture of how AI-driven tools stack up against conventional methods in real-world clinical settings. The review zeroed in on primary studies that used solid reference standards and provided enough data to assess or determine diagnostic performance, keeping the focus sharp and reliable.

2.2. Search Strategies

To evaluate the diagnostic accuracy of AI-based point-of-care testing (POCT) compared to traditional POCT, a thorough literature search was conducted across five major databases: PubMed, Google Scholar, ScienceDirect, IEEE Xplore, and Semantic Scholar. These were chosen for their extensive coverage of biomedical, clinical, and interdisciplinary research relevant to AI and diagnostics. PubMed, a go-to for peer-reviewed biomedical studies, was selected for its high- quality clinical research and precise search capabilities using Medical Subject Headings (MeSH) [20]. Google Scholar helped capture literature which are valuable for emerging fields like AI-POCT [21]. ScienceDirect provided access to technical and computer science literature, especially from Elsevier journals focused on medical device innovation. Semantic Scholar, with its AI-driven search and ranking, was ideal for finding recent, relevant studies at the intersection of machine learning and healthcare. IEEE Xplore, an online research repository was used because its repository focuses on research works on technology, engineering and computer science, which align greatly with this study.

The search covered January 2015 to April 2024, a period when AI in diagnostics really took off due to advances in machine learning and digital health [22]. This timeframe keeps the focus on modern AI methods and POCT platforms relevant to today's clinical needs [11]. Only English- language studies were included, using a mix of keywords like "artificial intelligence," "machine learning," "point-of-care testing," "diagnostic accuracy," "sensitivity," and "specificity," combined with Boolean operators (AND, OR) for precision. Beyond databases, manual searches of reference lists from included studies and reviews known as "backward snowballing" were conducted to catch any missed studies, especially those not well-indexed or using varied terminology [23]. This approach ensures a comprehensive and robust review, minimizing publication bias and capturing the full scope of relevant research.

Table 1 Search strategy for databases used in the systematic review on the diagnostic accuracy of point-of-care testing (POCT).

Table 1: Databases for search queries/Boolean functions

Database	Search query/Boolean function	Filter	Search Date
PubMed	((“Point-of-Care Systems”[MeSH Terms] OR “POCT” OR rapid diagnostic test OR “lateral flow immunoassay”) AND (“Sensitivity and Specificity”[MeSH Terms] OR diagnostic accuracy OR “predictive value”)) NOT review[Publication Type]	Article Type: Clinical Trial, Evaluation Study, Comparative Study Species: Humans Publication Dates: 2015-2024	17^{th} April, 2025
Google Scholar	(“point-of-care testing” OR “POCT” OR rapid diagnostic test OR lateral flow test) AND (“diagnostic accuracy” OR “sensitivity” OR specificity) -review -meta-analysis	2015-2024	18^{th} April, 2025
ScienceDirect	“point-of-care testing” OR “rapid diagnostic test” AND (“diagnostic accuracy” OR “sensitivity” OR specificity) NOT review NOT “systematic review”	for Research Articles Select subject areas like Medicine, Biochemistry, or, Health Sciences Sort by Newest First	19^{th} April, 2025
IEEE Xplore	(“artificial intelligence” OR AI OR “machine learning” OR “deep learning”) AND (“point of care” OR POCT OR “point-of-care testing”) AND (traditional OR conventional) AND (diagnos* OR diagnostic performance OR accuracy OR sensitivity OR specificity) AND (comparative OR comparison OR evaluate* OR assess*)	Journals Open access only	12^{th} December, 2025
Semantic Scholar	(“point-of-care testing” OR “POCT” OR rapid diagnostic test) AND (“diagnostic accuracy” OR “sensitivity” OR “specificity”) - review	Exclude Review Articles with filters Choose Clinical Medicine, Biology,or Diagnostic Testing as focus fields Restrict to recent years (especially post-2015)	17^{th} April, 2025
Manual Search (Reference Lists)	Screening of references from included reviews and eligible full-text studies	Peer-reviewed full texts only	17^{th}-20^{th} April, 2025

The Table 1 outlines the databases searched, Boolean search terms and strings, applied filters, and search dates. PubMed, Google Scholar, ScienceDirect, IEEE Xplore, and Semantic Scholar were systematically queried, along with a manual search of reference lists from relevant studies.

This table provided a transparent and reproducible search strategy, ensuring comprehensive coverage of studies on POCT diagnostic performance. The use of MeSH terms, Boolean operators, and exclusion filters enhances precision. Date restrictions (2015–2024) prioritize recent evidence, while manual reference screening minimizes omission of relevant studies. The strategy aligns with best practices for systematic reviews in diagnostic test accuracy.

2.3. Eligibility Criteria

Studies were included in the review if they met strict criteria: (1) involved human participants; (2) evaluated either AI-based point-of-care testing (AI POCT) or traditional POCT; (3) reported diagnostic accuracy metrics like sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), or area under the curve (AUC); and (4) were peer-reviewed primary research articles with full-text access, conference publications and preprints. Given the challenges in finding direct comparisons between AI-enhanced POCT and traditional POCT, this systematic review was designed to include studies that evaluated AI-enhanced POCT or traditional POCT separately. The review aimed to make indirect comparisons between the two methods. The focus was always on assessing the diagnostic accuracy (e.g., sensitivity, specificity, AUC) for each method individually and making a comparison of results across studies.

Studies were excluded if they: (1) focused only on non-POCT lab-based diagnostics; (2) used simulated data, computational models, or animal experiments; or (3) were abstracts, editorials, opinion pieces. Studies without full-text access were also excluded to ensure thorough methodological review. Only English-language studies were included due to the reviewers’ language limitations, lack of translation resources, and evidence that excluding non-English studies has minimal impact on diagnostic accuracy reviews [24, 25].

While preprints and conference publications were allowed due to limited studies in this emerging field, focusing mainly on peer-reviewed scholarly publications ensured scientific credibility and rigor, as journal publication evaluation process filters out methodological flaws and unsubstantiated claims common in non-scholarly publications [26]. This approach strengthens the reliability of the findings, providing a solid evidence base for clinical and policy decisions.

2.4. Data Extraction and Management

Two reviewers independently extracted data using a standardized form, which was tested beforehand to ensure it was clear and consistent. They collected details like study title, authors, publication year, country, disease, sample size, clinical setting, AI algorithm type, POCT platform, comparison method, and diagnostic performance outcomes (e.g., sensitivity, specificity). Any disagreements were settled through discussion or by a third reviewer. Data were organized in Excel and managed with Mendeley for accurate citation tracking and cross-referencing.

2.5. Quality Assessment

The quality and potential bias of each study were evaluated using the Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-2) tool, which assessed four areas: patient selection, index test, reference standard, and flow and timing [27]. Each area was checked for risk of bias and applicability concerns, with studies rated as low, high, or unclear risk. Results were summarized in a table and visualized to spotlight potential bias issues. The completed QUADAS 2 Assessment Summary form ensured transparent reporting and informed sensitivity analyses based on study quality. Passing the quality assessment required at least three (3) "low" in the four assessed parameters.

Table 2: Quality assessment of included studies using the QUADAS-2 (Quality Assessment of Diagnostic Accuracy Studies-2) tool

Authors/Year	Patient Selection	Index Test	Reference Standard	Flow & Timing
Lee et al. [28]	Low	Low	Low	Low
Pilarowski et al. [29]	Low	Low	low	Unclear
Stringer et al. [30]	Low	Low	Low	Low
Florkowski et al. [25]	High	Low	Unclear	Low
Bermejo-Peláez et al. [31]	Low	Low	Low	Low
Singh et al. [32]	Low	Low	Low	Low
Zalama-Sánchez et al. [33]	Low	Low	Low	Low
Zhou et al. [34]	Unclear	Low	high	Low
Shapiro et al. [35]	Low	High	high	Low
Wang et al. [36]	High	Unclear	Unclear	Unclear
Worasith et al. [37]	Low	Low	Low	Low
Papadopoulou et al. [38]	Low	Low	Low	Low
Ong & Poljak, [39]	High	High	Unclear	Unclear

The Table 2 above evaluated risk of bias across four domains: Patient Selection, Index Test, Reference Standard, and Flow & Timing, with judgments of Low, High, or Unclear risk.

This table systematically assesses methodological quality, showing that seven (7) studies had low risk of bias and one (1) low-moderate risk of bias (one unclear and all low) across all domains, supporting their reliability. The remaining studies had high or unclear risk in patient selection or reference standards, potentially limiting their validity. Overall, the results indicate predominately high-quality evidence but shows specific studies with low quality. Studies with all "low", and "one unclear and all low" were considered for data extraction. Studies outside this risk threshold were excluded from the extraction.

2.6. Data Synthesis and Analysis

A narrative synthesis approach was adopted due to the diversity of study designs, disease conditions, diagnostic platforms, and reported outcome measures. The included studies varied in their clinical targets, AI models, and POCT modalities, which made statistical pooling inappropriate for meta-analysis. Instead, extracted data were summarized descriptively and organized in both tabular and graphical formats to enable comparative evaluation of diagnostic performance between AI-enhanced and traditional point-of-care testing (POCT) systems. Key diagnostic metrics such as sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the curve (AUC) were extracted and reported. These metrics were compiled into summary tables that included study characteristics (e.g., author, year, sample size, index test, reference standard, target condition, and POCT type) and diagnostic insights, including additional context-specific remarks. To enhance visual comparison across studies, three figures were developed. Bar charts were used to illustrate sensitivity and specificity values of AI and traditional POCTs by study and diagnostic target. A third figure displayed AUC values was reported, allowing graphical comparison of diagnostic accuracy across methods and conditions. Color-coding was used to distinguish between AI-based and traditional POCT systems in all figures. All visualizations were descriptive and intended to highlight performance trends rather than quantify statistical significance. Additionally, the quality of each included study was assessed using the QUADAS-2 tool. Risk of bias assessments were recorded in a separate table and used to inform the interpretability of findings during synthesis. No statistical tests for heterogeneity or publication bias were performed. All data synthesis steps were conducted manually and reviewed by two independent reviewers to ensure consistency and transparency.

2.7. Ethical Considerations

This systematic review used only previously published, publicly available data, so no new patient information was collected or handled, so formal ethical approval was not needed. No identifiable personal data were used. The review followed ethical standards for secondary research, ensuring transparency, reproducibility, and responsible use of published studies. To maintain objectivity, steps were taken to reduce bias in study selection, data extraction, and synthesis. All authors declared no conflicts of interest, and the review adhered to ethical guidelines for literature-based research. Also, authors had no prior involvement with commercial AI POCT platforms.

3. Results

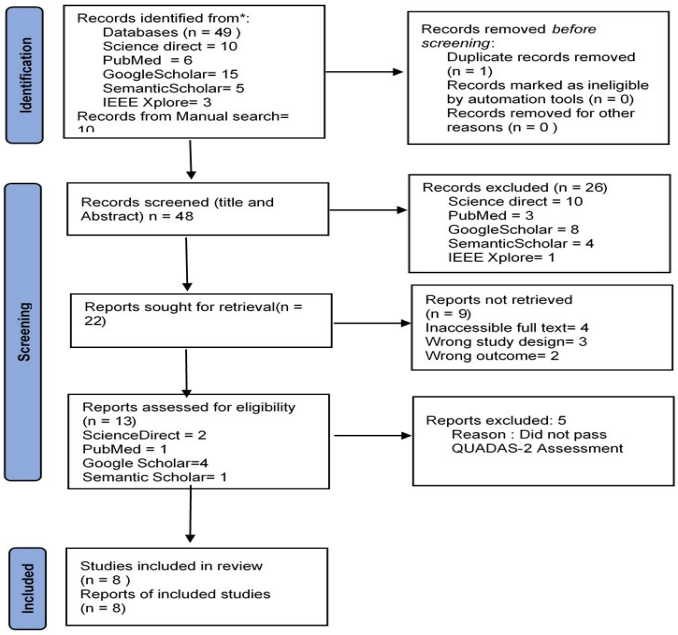


Figure 1: PRISMA Flow Diagram of Study Selection Process

Figure 1 shows the flow diagram summarizes the selection process of studies included in the systematic review, based on PRISMA 2020 guidelines. A total of 49 records were identified through database and manual searches. After removing one duplicate, 48 unique records were screened by title and abstract. Of these, 26 were excluded for not meeting inclusion criteria. Full text screening was performed on the remaining 22 articles for eligibility, but 9 could not be retrieved due to inaccessibility, unsuitable study design and wrong outcomes. The remaining thirteen full-text articles were subjected to quality assessment, and 5 were excluded for not meeting the QUADAS-2 quality assessment threshold. Ultimately, 8 studies were included in the final synthesis.

Table 3: Characteristics of included studies evaluating point-of-care tests (POCTs)

Study (Author, Year)	Study Design	Sample Size	Index Test	Reference Standard	Target Condition	POCT Type
Pilarowski et al. [29]	Cross-sectional diagnostic accuracy	878	BinaxNOW Ag Card	RT-PCR	SARS-CoV-2	Antigen lateral flow
Worasith et al. [37]	Diagnostic accuracy with field trial	493	Urinary OV-RDT	FECT + ELISA	Opisthorchis viverrini	Urine antigen lateral flow
Papadopoulou et al. [38]	Nested case-control diagnostic study	111	Kosmos HUD + AI	Biplane Simpson's method	Impaired LVEF	AI-guided handheld echo
Singh et al. [32]	Prospective diagnostic validation	446	Gazelle	CE-HPLC	β-thalassemia trait	Microchip electrophoresis
Lee et al. [28]	AI-enhanced diagnostic Validation	~2500 images	TIMESAVER AI + LFA	RT-PCR, lab tests	COVID-19, Influenza, hCG, TnI	AI-assisted Smartphone
Zalama-Sánchez et al. [33]	Prospective multicenter Cohort	201	Siemens Atellica® VTLi	Roche/Beckman hs-cTn assays	NSTEMI	hs-cTnI POC Analyzer
Stringer et al. [30]	Prospective diagnostic Accuracy	400	AI-enabled Butterfly IQ+	Standard fetal biometry	Gestational Age (GA)	AI-guided Ultrasound
Bermejo-Peláez et al. [31]	Prospective validation and field study	268 (field), 1165 (train/ validate)	TiraSpot app + AI	Visual interpretation by health professionals	SARS-CoV-2 (IgG, IgM, Ag)	AI-assisted LFA (smartphone)

Keys: BinaxNOW Ag Card= BinaxNOW COVID-19 Antigen Card; CE-HPLS= Capillary Electrophoresis-High-Performance Light Scattering; FECT- ELISA=Fecal Enzyme-Linked Immunorbent Assay; hs-cTnl POC Analyzer= High-Sensitivity Cardiac Troponin I Point-of-Care Analyzer; Impaired LVEF- Impaired Left Ventricular Ejection Fraction; Kosmos HUD + AI= Kosmos Heads-Up Display + Artificial Intelligence; NSTEMI= Non-ST-Segment Elevation Myocardial Infarction; RT-PCR= Reverse Transcription Polymerase Chain Reaction; SARS-CoV-2= Severe Acute Respiratory Syndrome Coronavirus 2; TIMESAVER AI + LFA= TIMESAVER Artificial Intelligence + Lateral Flow Assay; Urinary OVRDT= Urinary Ovulation Rapid Diagnostic Test.

The Table 3 above summarizes study design, sample size, index test, reference standard, target condition, and POCT type for each selected study.

This table provides a structured overview of key studies assessing various POCTs, highlighting their diagnostic accuracy against reference standards. The studies cover diverse conditions (e.g., SARS-CoV-2, parasitic infections, cardiac dysfunction) and POCT technologies (e.g., lateral flow assays, AI-guided ultrasound, microchip electrophoresis). The inclusion of different study designs (cross-sectional, prospective, AI-enhanced validation) reflects a broad evidence base, supporting the evaluation of POCT performance across clinical settings.

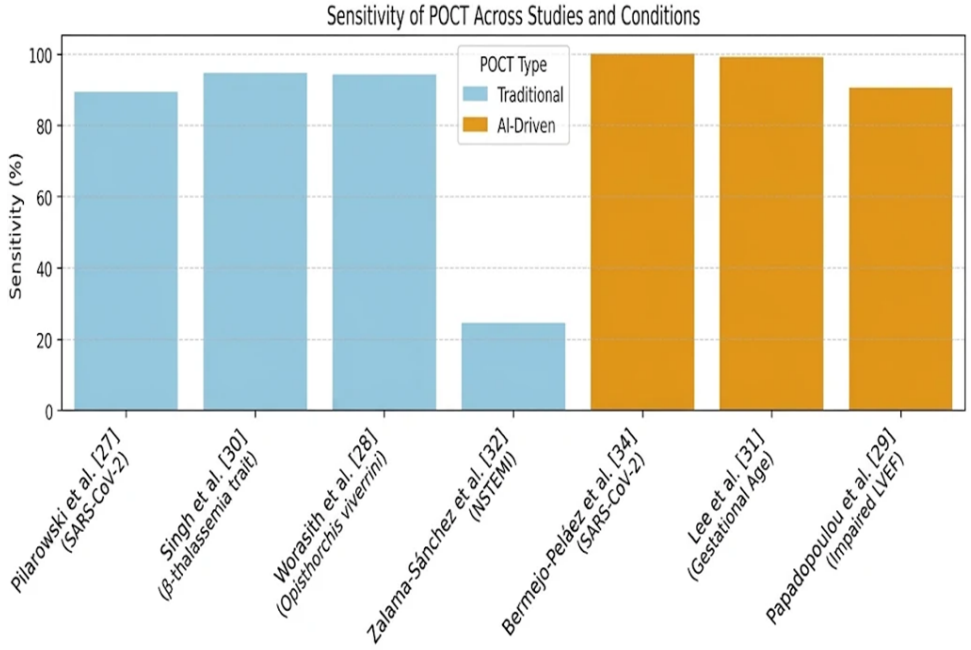


Figure 2: Sensitivity of Traditional and AI-Driven Point-of-Care Testing (POCT) methods across various clinical targets

Each bar represents a published study, with the corresponding target condition noted. Color coding differentiates between Traditional POCT (sky blue) and AI-driven POCT (orange). Sensitivity values reflect the proportion of true positive results correctly identified by each method.

In Figure 2 AI-driven, POCT generally demonstrated high sensitivity, with studies such as Bermejo-Peláez et al. [31] and Lee et al. [28] reporting sensitivity values of 99–100%. In contrast, most Traditional POCTs also performed well, except for Zalama-Sánchez et al. [33] which showed a notably low sensitivity (24.3%) for early NSTEMI detection.

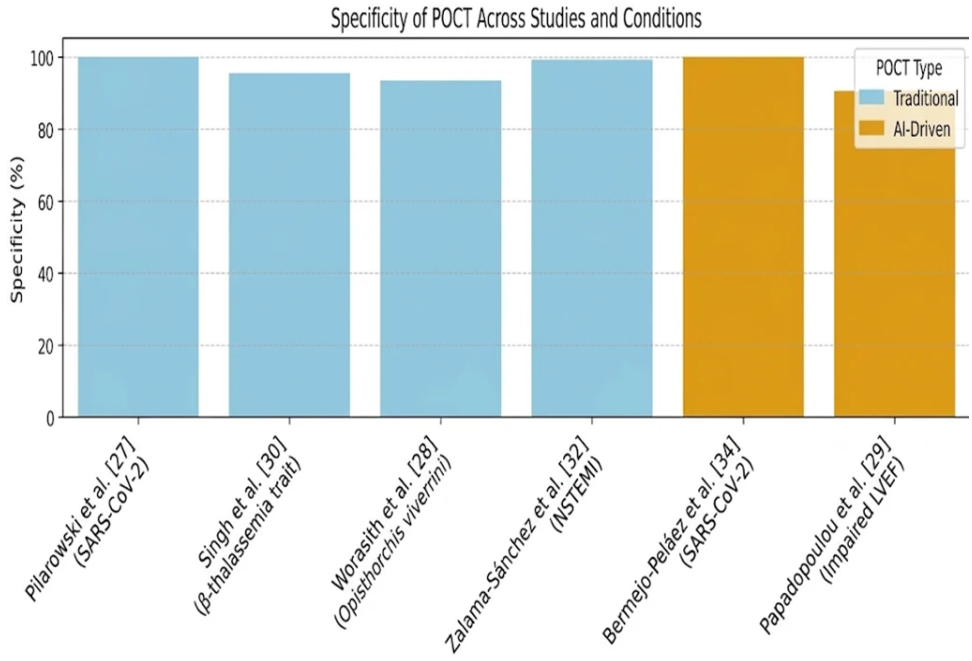


Figure 3: Specificity of Traditional and AI-Driven POCT methods by study and target condition

Specificity indicates the proportion of true negatives correctly identified. Bars are color-coded by POCT type, and study labels include both the citation and diagnostic target.

In Figure 3, Specificity values were generally high across all POCTs. Traditional POCT methods demonstrated specificity ranging from 93% to 99.9%. AI-driven POCTs maintained similarly high performance, with Bermejo-Peláez et al. [31] achieving 100%. Notably, Lee et al. [28] did not report specificity data, limiting interpretation of that model's performance.

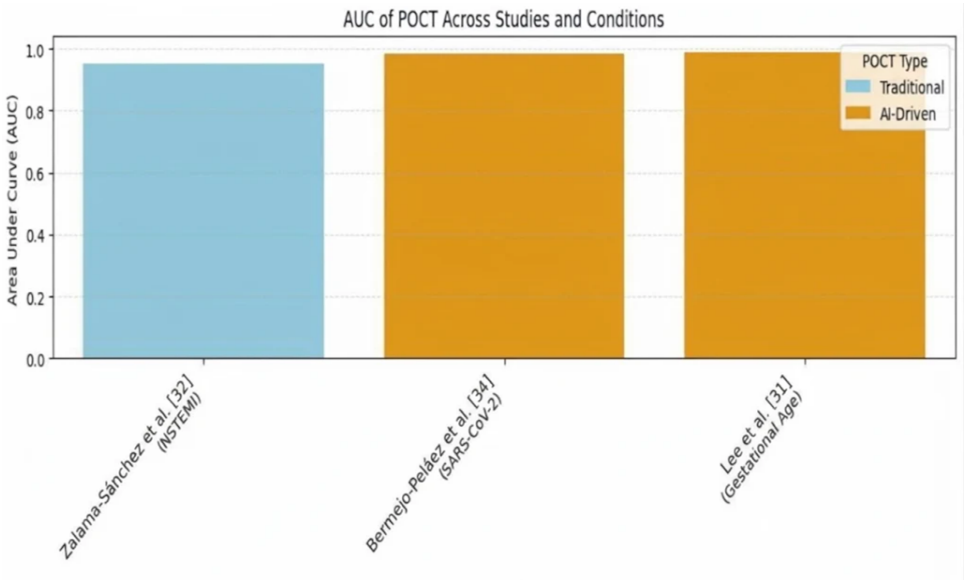


Figure 4: AUC of POCT Across Studies and Conditions

Figure 4 Diagnostic accuracy of POCT methods as measured by the Area Under the Curve (AUC) metric. The AUC values reflect the overall ability of each test to discriminate between diseased and non-diseased states. Only studies that reported AUC values are included.

In Figure 4, AI-driven POCT consistently exhibited high diagnostic accuracy, with AUC values of 0.985 [28] and, 0.99 [37]. Zalama-Sánchez et al. [33] also reported a high AUC (0.95) for a Traditional POCT in detecting NSTEMI.

Table 4: Result Table of Diagnostic Metrics

Study (Author, Year)	Target Condition	Other Metrics
Traditional POCT		
Pilarowski et al. [29]	SARS-CoV-2	Performance drops in low viral load
Singh et al. [32]	β-thalassemia trait	Microchip electrophoresis
Worasith et al. [37]	Opisthorchis viverrini	Urinary OV-RDT
Zalama-Sánchez et al. [33]	NSTEMI	PPV: up to 80.7%, NPV: $\sim$94%
AI-Driven POCT		
Bermejo-Peláez et al. [31]	SARS-CoV-2 (IgG, IgM, Ag)	-
Lee et al. [28]	Gestational Age (GA)	-
Papadopoulou et al. [38]	Impaired LVEF	AI-guided LVEF assessment

Keys: SARS-CoV-2= Severe Acute Respiratory Syndrome Coronavirus 2; NSTEMI= Non-ST-Segment Elevation Myocardial Infarction; LVEF= Impaired Left Ventricular Ejection Fraction; Urinary OV-RDT= Urinary Ovulation Rapid Diagnostic Test; PPV= Positive Predictive Value

The Table 4 summarizes additional diagnostic features and remarks reported by included studies on Traditional and AI-Driven Point-of-Care Testing (POCT) methods. The "Other Metrics" column captures context-specific diagnostic insights, such as limitations, techniques employed, or predictive values, which supplement core performance metrics (e.g., sensitivity, specificity, AUC).

While many studies focused on sensitivity and specificity, additional context-specific information enhances the understanding of each POCT's diagnostic value. For example, the traditional POCT evaluated by Zalama-Sánchez et al. [33] reported high predictive values despite low sensitivity, while Singh et al. [32] utilized microchip electrophoresis for β-thalassemia detection. AI-driven POCTs often did not report supplementary metrics but emphasized automated or AI-guided diagnostic assistance, reflecting their evolving nature and potential in enhancing diagnostic precision.

4. Discussion

The studies reviewed suggest that Point-of-Care Testing (POCT) systems augmented with AI technologies may maintained a superior level of accuracy and sensitivity greater across various conditions than traditional POCT systems. For example, Bermejo-Peláez et al. [31] used TiraSpot's AI app and reported near 100% sensitivity and specificity in SARS-CoV-2 antigen and antibody detection. Those results were significantly better than the outcomes of field-situated lateral flow assays that were read manually. AI's accuracy in interpreting lateral flow results is often attributed to the ability to identify faint positive lines, which human analysts are prone to miss because of their subjectivity

and the influence of the surrounding setting. This aligns with findings by Turbé [40] where the use of AI integrated diagnostic applications reduced the incidence of false-negative results in HIV tests conducted in Sub-Saharan Africa, which allowed for timely intervention. Results were also presented by Lee et al. [28] where the TIMESAVER AI system displayed an outstanding performance resulting in AUCs of 0.99 and 0.97 for COVID-19 and Influenza respectively. Such eficiencia is seldom reported in traditional POCTs. Advanced deep learning techniques applied by TIMESAVER AI to complex visual data eliminates differences in judgement called by multiple evaluators. Ferguson et al. [41] and Khan et al. [17] support this conclusion, arguing that AI-powered POCT systems can detect subtle image features that human users may miss. The consistent diagnostic performance of these systems across multiple assays and disease states underscores the scalability and reliability of AI in diagnostics. POCTs, while effective and popular, have their shortcomings. Pilarowski et al. [29], for instance, analyzed the performance of the BinaxNOW COVID-19 antigen card and reported a sensitivity of 89% (for samples with Ct $\leq$30) and specificity of 99.9%. However, the test's performance in asymptomatic patients or patients with lower viral loads was much worse. This type of variability is a frequent limitation of tests that require visual interpretation and has been reported by Viswanathan et al. [42] and Schmidt-Erfurth et al. [8]. The problem arises from the interpretation of results, which is prone to a myriad of factors such as lighting, level of training of the user, exhaustion, and experience. As a result, these factors pose challenges for traditional POCTs in mass and decentralized screening where high levels of precision are needed. Still, in many low-resourced or emergency situations where digital infrastructure is absent, traditional POCT has a critical role to fill owing to its low cost, simplicity, and low training demands. Additionally, in some cases like specific antigen-based assays where the diagnostic signal is obvious, interpretation done by a human eye remains dependable and does not require AI assistance [43]. The disease scope in the reviewed studies ranged from acute infectious diseases like COVID-19 and opisthorchiasis to chronic and non-communicable conditions such as gestational age estimation and β-thalassemia trait detection. This diversity highlights the flexibility of both diagnostic paradigms but also precludes direct cross-study comparisons. Notably, traditional POCT has proven reliable in settings involving well-defined, binary biomarkers. For instance, Singh et al. [32] and Worasith et al. [37] reported sensitivities and specificities above 93% for β-thalassemia and urinary antigen detection, respectively. These tests benefit from clear-cut signal intensities that reduce interpretation ambiguity. The potential of AI technologies is especially notable in the analysis of imaging data. AI-enhanced echocardiographic evaluation, as reported by Papadopoulou et al. [38], showed diagnostic agreement with cardiologists regarding the detection of clinically significant heart diseases. AI interpretation of autofluorescence imaging aided earlier detection of infection in diabetic foot ulcers as Chen [44] noted, lowering the chances of developing septic conditions and the need for amputation. Grand View Research [5] corroborated these findings, reporting improved outcomes in the management of diabetic foot ulcers with the use of AI-powered monitoring systems in rural India. One of the most profound benefits of AI in point of care testing (POCT) is its capacity to eliminate variability in the analysis of diagnostic data. Visual assessment, often the primary technique used in POCT, is subjective and prone to many sources of error such as inadequate lighting, user tiredness, and even the user's level of training [45]. These issues do not exist with AI, as they use objective criteria to make automated interpretations. The work of Bermejo-Peláez et al. [31] demonstrated that the TiraSpot AI app enhanced the classification of weak positive results which decreased the false negative rate and improved the effectiveness of public health response during the pandemic. This finding is in line with work by Pillay et al. [46], who observed a 20% reduction in false negatives when using AI for dengue rapid tests in Southeast Asia. In certain cases, older generation POCT devices like the Siemens Atellica® VTLi do have digital readers integrated into them, but it is not sufficient for accurate diagnosis. Zalama-Sánchez et al. [33] highlighted that the Atellica® VTLi was able to achieve a specificity of over 98%, however, its sensitivity towards interpreting early NSTEMI changes was diagnosed to be under 25%. This showcases the need for advanced AI algorithms for machine learning based diagnostics rather than simple device upgrades. This research emphasizes the idea that sophisticated algorithms coupled with advanced machine learning techniques are crucial for clinical hardware to truly make an impact. Stringer et al. [30], for example, described an AI-powered portable ultrasound device that estimated a patient's age in terms of weeks with a significant error margin of 3.19 days, which is comparable to expert sonographers' average error of 3.03 days. Rather than diminish AI's significance, this equivalent performance highlights AI's capacity to democratize diagnostics—providing expert-level evaluations in resource-limited environments. Khan et al. [17] is in support of this argument, claiming that AI especially expands the lack of sufficient qualified personnel in these regions for obstetrics and neonatal care. The efficiency with which an individual can be diagnosed using smarter technologies, such as smartphone-based TiraSpot and TIMESAVER systems, is another important advantage of integration AI into POCT. Diagnosis is done in a matter of minutes, circumventing the waiting time associated with lab-diagnostic tests and conventional POCTs that need processing and interpretation through reading. In high-acuity environments like outbreaks of infectious diseases or urgent cardiac care, diagnostic speed is fundamental [16, 47]. As a case in point, emergency departments for patients with chest pain benefit significantly from AI POCT's fast diagnostic EV technologies during the critical first phase of triage which reduces door-to-treatment times. Such enhanced speed of diagnosis actually changes clinical outcomes. Chen et al. [44] used AI to interpret images of diabetic foot ulcers and detected early-stage infections which diminished the need for amputations. AI tools used for estimating the age of the fetus at different stages of pregnancy have made timely obstetric referrals possible that greatly improved the health of mothers and babies [48]. These advantages are even more striking for low-and middle-income countries (LMICs) where specialists are hard to get and the cost of delay in diagnosis can be life-threatening. AI POCT has its challenges, however. The initial investment for the equipment, cloud services, and application development may be considerable; however, there is potential for reduced spending in the long run due to a decrease in expensive retests, lowered reliance on central labs, and fewer diagnostic errors [49]. In addition, the over-dependence on AI systems without adequate clinical supervision raises concerns about algorithm bias, data privacy, and AI reliance. These problems are crucial in healthcare environments where regulatory supervision is limited, or digital skills are lower than average [50]. AI POCT has the potential to change how healthcare diagnostics are done. However, its adoption needs to be carefully evaluated in terms of the clinical setting, available infrastructure, and socio-economic factors influencing access. The traditional POCT will continue to be important in many areas for simplicity, low cost, and effectiveness in remote or emergency situations.

5. Conclusion

This systematic review shows that AI-enhanced point-of-care testing (POCT) often outperforms or matches traditional POCT in diagnostic accuracy across various diseases, boasting higher sensitivity, specificity, and AUC, especially for complex tasks like image analysis or detecting faint signals. AI's automation cuts down on human error, boosts consistency, and speeds up results, which can be a game-changer in resource-scarce or high-pressure settings. It also brings expert- level diagnostics to non-specialists, expanding access to quality care.

However, hurdles like infrastructure needs, algorithm biases, costs, and regulatory gaps must be tackled for safe and fair use. Rather than replacing traditional POCT, which shines for its simplicity, portability, and low cost, AI POCT should complement it, addressing gaps were precision, speed, or standardization matter most. A combined approach promises the most effective and inclusive diagnostic care tailored to diverse contexts.

Limitations

The application of AI is an emerging area in the field of medicine, and this research focused on directly comparing traditional diagnostic techniques and AI-supported techniques are limited. The number of included studies (8 studies) in this study were quite few to draw solid evidence from them- this is a notable limitation of this study. Another notable limitation was the fact that the studies included in this systematic review focused on various conditions, thus creating high variation among selected studies (heterogeneity) and complexity in comparison.

Recommendations

To get the most from AI-assisted point-of-care testing, we still have a few big boxes to check. First, we do not just need massive studies on real patients in clinics, homes and remote huts, so we know one result really works everywhere but we also need to statistically compare it diagnostic performance with traditional POCT in a target condition at a time. This will bring more specific insight into their relative diagnostic performance. Second, the basics-power, internet, even simple phone access-have to be in place, especially where health budgets shrink fast. Third, the code itself should be clear and balanced, written from data that includes every skin tone, age and gender. Fourth, staff must learn to slip these tools into daily rounds without feeling their brains are already too full. Fifth, watchdogs have to draft rules that keep an eye on the AI after it goes live, not just before. Yes, the initial bill is steep, but the long-term savings from fewer missed clues and repeat tests could pay the rent. In the end, doctors, coders and policy makers need to sit at the same table if rapid, reliable testing is going to be an everyday option for everyone. Addressing these priorities now will help close the gap between shiny lab demos and the corner clinic, making fast, accurate tests something any patient can expect.

List of Abbreviations

AI – Artificial Intelligence
AUC – Area Under Curve
BinaxNOW Ag Card – BinaxNOW COVID-19 Antigen Card
CE-HPLS – Capillary Electrophoresis-High-Performance Light Scattering
CLIA – Clinical Laboratory Improvement Amendments
FECT-ELISA – Fecal Enzyme-Linked Immunosorbent Assay
hs-cTnI POC Analyzer – High-Sensitivity Cardiac Troponin I Point-of-Care Analyzer Impaired
LVEF – Impaired Left Ventricular Ejection Fraction
Kosmos HUD + AI – Kosmos Heads-Up Display + Artificial Intelligence
MAE – Mean Absolute Error
MeSH – Medical Subject Headings
NPV – Negative Predictive Value
NSTEMI – Non-ST-Segment Elevation Myocardial Infarction
POCT – Point of Care Testing
PPV – Positive Predictive Value
PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QUADAS-2 – Quality Assessment of Diagnostic Accuracy Studies 2
RT-PCR – Reverse Transcription Polymerase Chain Reaction
SARS-CoV-2 – Severe Acute Respiratory Syndrome Coronavirus 2
TIMESAVER AI + LFA – TIMESAVER Artificial Intelligence + Lateral Flow Assay Urinary
OVRDT – Urinary Ovulation Rapid Diagnostic Test

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References

[1] A. G. Lopez. *Real-Time Imaging for Microfluidic Applications*. PhD thesis, Hochschule Niederrhein, 2017. URL https://doi.org/10.13140/RG.2.2.33187.48165/1.

[2] C. P. Price. Point of care testing. *BMJ*, 322(7297):1285–1288, May 2001. URL https://doi.org/10.1136/bmj.322.7297.1285.

[3] G. A. Posthuma-Trumpie, J. Korf, and A. van Amerongen. Lateral flow (immuno) assay: its strengths, weaknesses, opportunities and threats. A literature survey. *Analytical and Bioanalytical Chemistry*, 393(2):569–582, January 2009. URL https://doi.org/10.1007/s00216-008-2287-2.

[4] E. L. Lewandrowski, S. Yeh, J. Baron, J. B. Crocker, and K. Lewandrowski. Implementation of point-of-care testing in a general internal medicine practice: A confirmation study. *Clinica Chimica Acta.*, 473:71–74, October 2017. URL https://doi.org/10.1016/j.cca.2017.08.019.

[5] Grand View Research. Point-of-care testing market size share & trends analysis report, 2023-2030, 2023. URL https://www.grandviewresearch.com/industry-analysis/point-of-care-poc-diagnostics-market.

[6] M. Kardjadj. Advances in point-of-care infectious disease diagnostics: Integration of technologies, validation, artificial intelligence, and regulatory oversight. *Diagnostics*, 15(22):2845, 2025. URL https://doi.org/10.3390/diagnostics15222845.

[7] J. Holden, J. Goheen, M. Jett-Goheen, M. Barnes, Y. H. Hsieh, and C. A. Gaydos. An evaluation of the SD Bioline HIV/syphilis duo test. *International Journal of STD & AIDS*, 29(1):57–62, January 2018. URL https://doi.org/10.1177/0956462417717649.

[8] U. Schmidt-Erfurth, S. M. Waldstein, S. Klimscha, A. Sadeghipour, X. Hu, B. S. Gerendas, A. Osborne, and H. Bogunović. Prediction of individual disease conversion in early AMD using artificial intelligence. *Investigative Ophthalmology & Visual Science*, 59(8):3199–3208, July 2018. URL https://doi.org/10.1167/iovs.18-24106.

[9] S. Katzenschlager, L. E. Brümmer, S. Schmitz, H. Tolle, K. Manten, M. Gaeddert, C. Erdmann, A. Lindner, F. Tobian, M. Grilli, and N. R. Pollock. Performance of SARS-CoV-2 antigen- detection rapid diagnostic tests for COVID-19 self-testing and self-sampling in comparison to molecular and professional-use antigen tests: A systematic review and meta-analysis. *Research Square*, 2023. URL https://doi.org/10.21203/rs.3.rs-3263909/v1.

[10] J. R. Choi, J. Hu, S. Feng, W. A. Abas, B. Pingguan-Murphy, and F. Xu. Sensitive biomolecule detection in lateral flow assay with a portable temperature–humidity control device. *Biosensors and Bioelectronics*, 79:98–107, May 2016. URL https://doi.org/10.1016/j.bios.2015.12.005.

[11] E. J. Topol. High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1):44–56, January 2019. URL https://doi.org/10.1038/s41591-018-0300-7.

[12] T. Eche, L. H. Schwartz, F. Z. Mokrane, and L. Dercle. Toward generalizability in the deployment of artificial intelligence in radiology: role of computation stress testing to overcome underspecification. *Radiology: Artificial Intelligence*, 3(6):e210097, October 2021. URL https://doi.org/10.1148/ryai.2021210097.

[13] A. Bastawrous, M. E. Giardini, N. M. Bolster, T. Peto, N. Shah, I. A. Livingstone, H. A. Weiss, S. Hu, H. Rono, H. Kuper, and M. Burton. Clinical validation of a smartphone-based adapter for optic disc imaging in Kenya. *JAMA Ophthalmology*, 134(2):151–158, February 2016. URL https://doi.org/10.1001/jamaophthalmol.2015.4625.

[14] A. Tufail, C. Rudisill, C. Egan, V. V. Kapetanakis, S. Salas-Vega, C. G. Owen, A. Lee, V. Louw, J. Anderson, G. Liew, and L. Bolter. Automated diabetic retinopathy image assessment software: diagnostic accuracy and cost-effectiveness compared with human graders. *Ophthalmology*, 124(3):343–51, March 2017. URL https://doi.org/10.1016/j.ophtha.2016.11.014.

[15] P. Rajpurkar, E. Chen, O. Banerjee, and E. J. Topol. AI in health and medicine. *Nature Medicine*, 28(1):31–38, 2022. URL https://doi.org/10.1038/s41591-021-01614-0.

[16] E. Wu, K. Wu, R. Daneshjou, D. Ouyang, D. E. Ho, and J. Zou. How medical AI devices are evaluated: limitations and recommendations from an analysis of FDA approvals. *Nature Medicine*, 27(4):582–584, April 2021. URL https://doi.org/10.1038/s41591-021-01312-x.

[17] A. I. Khan, M. Khan, and R. Khan. Artificial intelligence in point-of-care testing. *Annals of Laboratory Medicine*, 43(5):401–407, September 2023. URL https://doi.org/10.3343/alm.2023.43.5.401.

[18] S. K. R. Vuruma, A. Margetts, J. Su, F. Ahmed, and B. Srivastava. From cloud to edge: rethinking generative AI for low-resource design challenges, 2024. URL https://arxiv.org/html/2402.12702v1. arXiv [Preprint].

[19] A. Mourya, B. Jobanputra, and R. Pai. AI-powered clinical trials and the imperative for regulatory transparency and accountability. *Health and Technology*, 14(1):1071–1081, 2024. URL https://doi.org/10.1007/s12553-024-00904-0.

[20] M. E. Falagas, E. I. Pitsouni, G. A. Malietzis, and G. Pappas. Comparison of PubMed, Scopus, web of science, and Google scholar: strengths and weaknesses. *The FASEB Journal*, 22(2):338–342, February 2008. URL https://doi.org/10.1096/fj.07-9492lsf.

[21] G. Halevi, H. Moed, and J. Bar-Ilan. Suitability of Google Scholar as a source of scientific information and as a source of data for scientific evaluation—Review of the literature. *Journal of Informetrics*, 11(3):823–834, August 2017.

[22] A. Esteva, A. Robicquet, B. Ramsundar, V. Kuleshov, M. DePristo, K. Chou, C. Cui, G. Corrado, S. Thrun, and J. Dean. A guide to deep learning in healthcare. *Nature Medicine*, 25(1):24–29, January 2019. URL https://doi.org/10.1038/s41591-018-0316-z.

[23] T. Greenhalgh and R. Peacock. Effectiveness and efficiency of search methods in systematic reviews of complex evidence: audit of primary sources. *BMJ*, 331(7524):1064–1065, November 2005. URL https://doi.org/10.1136/bmj.38636.593461.68.

[24] A. Morrison, J. Polisena, D. Husereau, K. Moulton, M. Clark, M. Fiander, M. Mierzwinski-Urban, T. Clifford, B. Hutton, and D. Rabb. The effect of English-language restriction on systematic review-based meta-analyses: a systematic review of empirical studies. *International Journal of Technology Assessment in Health Care*, 28(2):138–144, April 2012. URL https://doi.org/10.1017/s0266462312000086.

[25] C. Florkowski, A. Don-Wauchope, N. Gimenez, K. Rodriguez-Capote, J. Wils, and A. Zemlin. Point-of-care testing (POCT) and evidence-based laboratory medicine (EBLM)–does it leverage any advantage in clinical decision making? *Critical Reviews in Clinical Laboratory Sciences*, 54(7-8):471–494, November 2017. URL https://doi.org/10.1080/10408363.2017.1399336.

[26] T. Jefferson, P. Alderson, E. Wager, and F. Davidoff. Effects of editorial peer review: a systematic review. *JAMA*, 287(21):2784–2786, June 2002. URL https://doi.org/10.1001/jama.287.21.2784.

[27] P. F. Whiting, A. W. Rutjes, M. E. Westwood, S. Mallett, J. J. Deeks, J. B. Reitsma, M. M. Leeflang, J. A. Sterne, P. M. Bossuyt, and Quadas-2 Group. QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies. *Ann Intern Med*, 155(8):529–536, October 2011. URL https://doi.org/10.7326/0003-4819-155-8-201110180-00009.

[28] S. Lee, J. S. Park, H. Woo, Y. K. Yoo, D. Lee, S. Chung, D. S. Yoon, K. B. Lee, and J. H. Lee. Rapid deep learning-assisted predictive diagnostics for point-of-care testing. *Nature Communications*, 15(1):1695, February 2024. URL https://doi.org/10.1038/s41467-024-46069-2.

[29] G. Pilarowski, P. Lebel, S. Sunshine, J. Liu, E. Crawford, C. Marquez, L. Rubio, G. Chamie, J. Martinez, J. Peng, and D. Black. Performance characteristics of a rapid SARS-CoV-2 antigen detection assay at a public plaza testing site in San Francisco, November 2020. URL https://doi.org/10.1101/2020.11.02.20223891. medRxiv [Preprint].

[30] E. Stringer, J. Smith, and L. Brown. AI-enhanced handheld ultrasound for gestational age estimation. *Ultrasound Obstet Gynecol*, 63(4):432–439, 2024. URL {https://doi.org/10.1002/uog.27543},.

[31] D. Bermejo-Peláez, D. Marcos-Mencía, E. Álamo, N. Pérez-Panizo, A. Mousa, E. Dacal, L. Lin, A. Vladimirov, D. Cuadrado, J. Mateos-Nozal, and J. C. Galán. A Smartphone-based platform assisted by artificial intelligence for reading and reporting rapid diagnostic tests: Evaluation study in SARS-CoV-2 lateral flow immunoassays. *JMIR Public Health and Surveillance*, 8(12):e38533, December 2022. URL https://doi.org/10.2196/38533.

[32] N. Singh, T. Seth, and J. Dass. Assessment of diagnostic accuracy of Gazelle: A point-of-care testing device for screening β-thalassemia trait. *The Indian Journal of Medical Research*, 160(2):194, October 2024. URL https://doi.org/10.25259/ijmr_1986_23.

[33] D. Zalama-Sánchez, C. del Pozo Vegas, A. Sanz-García, P. Á. de Santos-Castro, J. Presencio-Dominguez, P. González-Izquierdo, S. Sánchez-Ramón, L. T. Pinilla-Arribas, M. Baladrón-Segura, J. Cheayeb-Morán, and M. Fernandez-García. Diagnostic Performance of Point-of- Care High-Sensitivity Troponin in the Exclusion of Non-ST-Elevation Myocardial Infarction in the Emergency Department. *Journal of Personalized Medicine*, 14(7):762, July 2024. URL https://doi.org/10.3390/jpm14070762.

[34] P. Zhou, H. Liu, L. Gong, B. Tang, Y. Shi, C. Yang, and Z. Han. A faster detection method for high-sensitivity cardiac troponin—POCT quantum dot fluorescence immunoassay. *Journal of Thoracic Disease*, 11(4):1506–1513, April 2019. URL https://doi.org/10.21037/jtd.2019.03.25.

[35] N. I. Shapiro, M. R. Filbin, P. C. Hou, M. C. Kurz, J. H. Han, T. P. Aufderheide, M. A. Ward, M. S. Pulia, R. H. Birkhahn, J. L. Diaz, and T. L. Hughes. Diagnostic accuracy of a bacterial and viral biomarker point-of-care test in the outpatient setting. *JAMA Network Open*, 5(10):e2234588, October 2022. URL https://doi.org/10.1001/jamanetworkopen.2022.34588.

[36] S. Wang, Y. Liu, Y. Qiu, Q. Dou, Y. Han, M. Huang, K. Hong, B. Yang, X. Zhou, and Q. Dai. Saliva- based point-of-care testing techniques for COVID-19 detection. *Virologica Sinica*, 37(3):472, May 2022. URL https://doi.org/10.1016/j.virs.2022.04.004.

[37] C. Worasith, J. Sithithaworn, P. Wongphutorn, C. Homwong, K. Khongsukwiwat, A. Techasen, K. Y. Kopolrat, W. Loilome, N. Namwat, B. Thinkamrop, and C. Tawarungruang. Accuracy of a new rapid diagnostic test for urinary antigen detection and assessment of drug treatment in opisthorchiasis. *Infectious Diseases of Poverty*, 12(06):79–90, December 2023. URL https://doi.org/10.1186/s40249-023-01162-4.

[38] S. L. Papadopoulou, D. Dionysopoulos, V. Mentesidou, K. Loga, S. Michalopoulou, C. Koukoutzeli, K. Efthimiadis, V. Kantartzi, E. Timotheadou, and P. Styliadis I. Nihoyannopoulos. Artificial intelligence-assisted evaluation of cardiac function by oncology staff in chemotherapy patients. *European Heart Journal-Digital Health*, 5(3):278–287, May 2024. URL https://doi.org/10.1093/ehjdh/ztae017.

[39] D. S. Y. Ong and M. Poljak. Smartphones as mobile microbiological laboratories. *Clin Microbiol Infect*, 26(4):421–424, 2020. URL https://doi.org/10.1016/j.cmi.2019.09.026.

[40] V. Turbé, C. Herbst, T. Mngomezulu, S. Meshkinfamfard, N. Dlamini, T. Mhlongo, T. Smit, V. Cherepanova, K. Shimada, J. Budd, N. Arsenov, S. Gray, D. Pillay, K. Herbst, M. Shahmanesh, and R. A. McKendry. Deep learning of HIV field-based rapid tests. *Nat Med*, 27(7):1165–1170, 2021. URL https://doi.org/10.1038/s41591-021-01384-9.

[41] J. Ferguson, S. Dunn, and J. Best. Evaluation of rapid antigen tests for SARS-CoV-2 in community settings. *J Clin Virol*, 146:105052, 2022. URL https://doi.org/10.1016/j.jcv.2021.105052.

[42] V. Viswanathan, S. Govindan, B. Selvaraj, S. Rupert, and R. Kumar. A clinical study to evaluate autofluorescence imaging of diabetic foot ulcers using a novel artificial intelligence enabled noninvasive device. *The International Journal of Lower Extremity Wounds*, 23 (1):169–176, March 2024. URL https://doi.org/10.1177/15347346211047098.

[43] M. Laguna, M. Holgado, A. L. Hernandez, B. Santamaría, A. Lavín, J. Soria, T. Suarez, C. Bardina, M. Jara, F. J. Sanza, and R. Casquel. Antigen-antibody affinity for dry eye biomarkers by label free biosensing: comparison with the ELISA technique. *Sensors (Basel)*, 15 (8):19819–19829, 2015. URL https://doi.org/10.3390/s150819819.

[44] H. Chen, K. Liu, Z. Li, and P. Wang. Point of care testing for infectious diseases. *Clinica Chimica Acta*, 493:138–147, June 2019. URL https://doi.org/10.1016/j.cca.2019.03.008.

[45] S. van Delft, A. Goedhart, M. Spigt, B. van Pinxteren, N. de Wit, and R. Hopstaken. Prospective, observational study comparing automated and visual point-of-care urinalysis in general practice. *BMJ Open*, 6(8):e011230, 2016. URL https://doi.org/10.1136/bmjopen-2016-011230.

[46] T. S. Pillay, A. Khan, and S. Yenice. Artificial intelligence (AI) in point-of-care testing. *Clin Chim Acta*, 574:120341, 2025. URL https://doi.org/10.1016/j.cca.2025.120341.

[47] L. Zhang, Y. Wang, and X. Chen. AI-driven rapid HIV testing in sub-Saharan Africa. *Lancet HIV*, 10(3):e184–91, 2023. URL https://doi.org/10.1016/S2352-3018(22)00345-7.

[48] J. S. A. Stringer, T. Pokaprakarn, J. C. Prieto, B. Vwalika, S. V. Chari, N. Sindano, B. L. Freeman, B. Sikapande, N. M. Davis, Y. V. Sebastião, N. M. Mandona, E. M. Stringer, C. Benabdelkader, M. Mungole, F. M. Kapilya, N. Almnini, A. N. Diaz, B. A. Fecteau, M. R. Kosorok, S. R. Cole, and M. P. Kasaro. Diagnostic accuracy of an integrated AI tool to estimate gestational age from blind ultrasound sweeps. *JAMA*, 332(8):763–773, 2024. URL https://doi.org/10.1001/jama.2024.10770.

[49] S. S. Krishna. Economic evaluation of AI-driven diagnostic tools in healthcare. *International Journal of Scientific Research & Engineering Trends*, 8(6):566–574, 2022.

[50] S. M. Williamson and V. Prybutok. Balancing privacy and progress: a review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare. *Appl Sci*, 14(2):675, 2024. URL https://doi.org/10.3390/app14020675.