JASDG
JOURNAL FOR THE ADVANCEMENT OF SUSTAINABLE DEVELOPMENT GOALS
AN INTERNATIONAL PEER-REVIEWED, OPEN ACCESS JOURNAL
www.jasdg.com
Volume 1 Issue 4 Pages 4947-4963
ISSN: 3155-7546 (Online)
DOI: 10.5281/zenodo.24381589

ARTIFICIAL INTELLIGENCE APPLICATIONS IN CLINICAL MICROBIOLOGY: USES, BENEFITS, CHALLENGES, AND IMPLICATIONS FOR LABORATORY QUALITY CONTROL

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Volume 1 Issue 4 Pages 4947-4963

ISSN: 3155-7546 (Online)
DOI: 10.5281/zenodo.24381589

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ABSTRACT

Artificial intelligence (AI) is being implemented to expand diagnostic capabilities, improve laboratory efficiency, enhance quality monitoring, and improve patient care. The integration of AI and machine learning in laboratory procedures offers opportunities that may help improve diagnostic interpretation, detect errors, standardize testing processes, and strengthen quality assessment. This study describes the probable applications, benefits, and challenges of artificial intelligence (AI) technology and its continued use in clinical microbiology laboratories. A descriptive review was conducted based on the findings and discussions presented in the Proceedings of the Clinical Microbiology Open 2024, supported by literature on AI-assisted quality monitoring. The assessment covered AI applications in microscopic analysis, interpretation of cultures, identification of microorganisms, antimicrobial susceptibility testing and resistance prediction, molecular automation, and laboratory automation. Findings from a conference survey indicate that the majority of the respondents identified improved efficiency in testing as the greatest beneficial aspect of AI, while others identified that AI helps improve quality monitoring. The major challenges are implementation cost, data quality, personnel expertise, and regulatory requirements. This review highlights how standard artificial intelligence can support clinical microbiology by improving workflow efficiency and assisting laboratory professionals with interpretation. However, reliable, accurate, and timely laboratory results require human supervision, validation procedures, and ongoing quality monitoring.

Keywords: *artificial intelligence, quality control, microbiology, machine learning, laboratory quality monitoring*

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INTRODUCTION

Background of the Study

Clinical microbiology laboratories have an important role in the diagnosis, management, and prevention of infectious diseases. Laboratories perform a variety of procedures across the pre-analytical, analytical, and post-analytical phases. Each stage requires appropriate procedures, competent personnel, suitable equipment and reagents, and effective quality control (QC). Errors or deviations at any point may affect the accuracy and reliability of laboratory findings and may influence clinical decisions.

QC is an important aspect of microbiological testing because it ensures that laboratory procedures produce accurate and consistent results. QC activities include monitoring of culture media, reagents, microorganisms, testing procedures, and personnel performance. Any deviation in these areas may affect the accuracy of laboratory findings and lead to inappropriate diagnostic interpretations. Because clinicians rely on timely and trustworthy microbiological results to select treatment and manage infection control, the dependability of each step in the testing process is a matter of patient safety as well as laboratory efficiency.

However, laboratories still face difficulties and challenges such as increasing workloads, complex diagnostic procedures, shortage of laboratory personnel, and the need for faster turnaround times. Current laboratory practice still requires the manual reading of culture plates, microscopic studies, and molecular diagnosis findings. To maintain laboratory standards and quality, technical expertise and ongoing surveillance of these activities are required. These persistent challenges make exploring new technologies such as artificial intelligence both timely and practical, as laboratories seek ways to maintain quality without proportionally increasing their workforce.

With recent advances in computational methods, AI has become a practical area of interest for clinical microbiology. AI includes computational approaches that identify patterns, classify data, and generate predictions from images, laboratory measurements, molecular outputs, or genomic information. Machine learning (ML), a major branch of AI, allows algorithms to learn relationships from data rather than relying only on fixed rules. These methods have been applied to microbial identification, culture interpretation, microscopy, antimicrobial resistance prediction, and laboratory workflow analysis (Alsulimani et al., 2024; Asnicar et al., 2024; Xu et al., 2025).

AI has emerged as a promising tool for enhancing laboratory operations and quality monitoring. AI refers to computational systems designed to perform tasks commonly associated with human reasoning, pattern recognition, or decision support. In clinical microbiology, this method may be applied to digital images, laboratory information, molecular test outputs, and microbiological or genomic data. Potential applications include bacterial colony recognition, Gram-stain interpretation, parasite detection, bacterial growth monitoring, antimicrobial resistance prediction, and laboratory workflow automation (Dien Bard et al., 2025).

Dien Bard et al. (2025) showed that AI has numerous potential applications in clinical microbiology. These include identifying bacterial colonies, interpreting Gram stains, identifying parasites, predicting antimicrobial resistance, and automating laboratory processes. These technologies may help reduce repetitive manual tasks, improve testing competence, and support the interpretation of laboratory findings.

Total laboratory automation can provide the infrastructure for digital image capture and algorithm-assisted interpretation. The benefits of automation depend on integrating instruments, software, consumables, and quality monitoring processes. Fischer et al. (2026) discussed the need for integrated internal quality control in automated microbiology workflows, while DeYoung et al. (2022) emphasized that AI-based culture-plate interpretation requires clearly defined intended uses and appropriate algorithm development.

The application of AI in monitoring bacterial growth has also been studied. In routine bacteriology, the reading and processing of sterile plates remains a significant part of the workload, as sterile plates account for 30%–40% of plates (Jacot et al., 2024). Jacot et al. (2024) created and validated an AI-based algorithm for detecting bacterial growth in microbiology laboratories. Using 3,844 culture plates, the study demonstrated that AI-based algorithms achieve high sensitivity in detecting bacterial growth. Thus, AI-assisted culture monitoring could be a valuable tool for optimizing plate-reading processes and identifying specimens that need attention.

Similarly, Signoroni et al. (2023) explored the potential of hierarchical AI to interpret culture plates globally in digital microbiology. Their study found that AI could detect and interpret patterns in bacterial growth, making microbiological tests more accurate and precise. Their work was set against the growing adoption of full laboratory automation, which generates large streams of digital plate images that must be interpreted (Signoroni et al., 2023).

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AI is also being investigated for laboratory quality monitoring. Machine-learning approaches to patient-based real-time quality control (PBRTQC) can analyze patient-result distributions and flag patterns that may indicate analytical shifts or errors. Lorde et al. (2024) reviewed applications for detecting analytical and pre-analytical errors, while Dong et al. (2024) compared an AI-based PBRTQC model with a traditional approach. These systems may provide an additional layer of surveillance, but they do not replace internal quality control materials, calibration, proficiency testing, or other established quality management activities.

In addition, Duan et al. (2024) discussed next-generation patient-based real-time quality control models, highlighting the potential of advanced techniques for continuous quality surveillance in healthcare. Zhou et al. (2022) also demonstrated the use of traceable machine learning for timely control using patient data.

MacLean and Gunson (2024) also reported that machine learning can help simplify and standardize quantitative multiplex polymerase chain reaction (PCR) testing. Their work demonstrated that using machine learning to optimize and standardize molecular diagnostics can improve consistency and accuracy when interpreting results.

AI and ML have also been applied to antimicrobial resistance (AMR) analysis. Models can examine genomic sequences, antimicrobial susceptibility data, and clinical information to identify associations with resistance phenotypes. These approaches may support surveillance and stewardship, but predictions must be assessed against appropriate reference methods and should not be treated as a substitute for validated antimicrobial susceptibility testing (Ardila et al., 2024; Bilal et al., 2025; Gerada et al., 2024).

Despite these advantages, implementing AI in clinical microbiology laboratories has challenges. These challenges include high implementation costs, limited technical expertise to use AI, data privacy protection, and ongoing validation. The laboratory must ensure that artificial intelligence systems are suitable for its testing processes and meet quality standards before being put into use.

According to Fischer et al. (2026), full automation of these devices is rarely produced by a single manufacturer. As a result, standardized and cohesive operation of devices for AI applications is still difficult to implement; the same goes for the reagents used during the automation process. Integrating automated instruments and AI applications is not always straightforward because platforms may differ in their software, reagents, data formats, and operational requirements. Laboratories therefore need a coordinated quality framework to verify system performance, identify software or instrument-related changes, document deviations, and ensure that AI-generated outputs remain subject to appropriate professional review (Fischer et al., 2026; DeYoung et al., 2022).

Statement of the Problem

The literature on AI in clinical microbiology spans several application areas and several kinds of publications, from a meeting proceedings report to technical development and validation studies and narrative or systematic reviews. For a microbiology laboratory considering AI, the practical question is not only what AI can do, but what it can contribute to quality control, what kind of evidence supports each application, and what conditions must be met before it is used in routine testing. This review responds to that question by bringing the reviewed applications, benefits, and challenges together within a quality-control perspective.

Objectives of the Study

Given these developments, this descriptive review examined AI as an emerging technology in clinical microbiology. It focused on its applications in image-based analysis, culture interpretation, microorganism detection, molecular diagnostic workflows, antimicrobial resistance prediction, and laboratory quality monitoring. It also considered the benefits, limitations, and requirements for responsible implementation. Specifically, the review aimed to:

1. describe the probable applications of AI in clinical microbiology and in laboratory quality control, including image-based analysis, culture interpretation, microorganism detection, molecular diagnostic workflows, antimicrobial resistance prediction, and laboratory quality monitoring;
2. identify the potential benefits of AI implementation in microbiology laboratories;
3. identify the challenges, limitations, and requirements for the responsible and continued use of AI in clinical microbiology laboratories; and
4. derive implications and recommendations for laboratory practice, including resource-limited settings, and for future research.

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Conceptual Framework of the Review

The review was organized using an Input–Process–Output (IPO) framework (Figure 1), consistent with its descriptive design. The Input consisted of the primary source (Dien Bard et al., 2025) and the supplementary peer-reviewed literature on AI in clinical microbiology and laboratory quality monitoring. The Process comprised the review and extraction of information, its grouping into six themes, and a qualitative descriptive synthesis. The Output consisted of the synthesized applications, benefits, and challenges of AI in microbiology laboratory quality control, and the conclusions and recommendations derived from them.

Figure 1. Conceptual Framework of the Review

INPUT	PROCESS	OUTPUT
• Primary source: Dien Bard et al. (2025) • Supplementary peer-reviewed literature on AI in clinical microbiology • Literature on patient-based real-time quality control and laboratory automation	• Review of the primary and supplementary publications • Extraction and grouping of information into six themes • Qualitative descriptive synthesis • Interpretation in relation to quality control practice	• Applications, benefits, and challenges of AI in microbiology laboratory quality control • Implementation considerations • Conclusions and recommendations

Significance of the Study

The findings of this review may be of value to the following:

Laboratory professionals. Medical technologists and microbiologists may use the synthesis to understand where AI-assisted tools can support, but not replace, their interpretive and quality-monitoring work, and what responsibilities remain with them.

Laboratory managers and quality officers. The review outlines the validation, monitoring, and governance requirements that should be considered before AI tools are adopted, which may support planning, budgeting, and quality management decisions.

Educators and trainers. The organized overview may serve as a reference for introducing AI concepts and their quality implications in laboratory science education and continuing professional development.

Health facility administrators and policymakers. The discussion of costs, personnel expertise, data governance, and regulatory considerations may inform institutional policies and phased adoption strategies, particularly in resource-limited settings.

Researchers and technology developers. The identified limitations and implementation considerations point to areas where further evaluation, reproducibility studies, and cost-effectiveness research are needed.

Scope and Delimitation of the Study

This review focused on the applications of AI, including machine learning, in clinical microbiology and in microbiology laboratory quality control, as reported in the proceedings report by Dien Bard et al. (2025) and the supplementary literature identified in the original manuscript. It covered image-based analysis, bacterial culture and growth interpretation, AI-assisted microscopy and microorganism identification, antimicrobial resistance analysis and prediction, molecular diagnostic interpretation and automation, and patient-based real-time quality monitoring, together with the reported benefits and challenges of implementation. The review was descriptive and literature-based. It was not a systematic review and did not involve a comprehensive database search, formal critical appraisal, or risk-of-bias assessment. It did not involve laboratory experiments, human participants, or the collection of new data, and numerical findings were reported as presented in the original publications rather than recalculated or pooled.

Definition of Terms

The terms used in this review are defined below as they are understood in the reviewed literature and used in this manuscript.

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Artificial intelligence (AI). Computational systems designed to perform tasks commonly associated with human reasoning, pattern recognition, or decision support. In this review, AI refers to such systems applied to digital images, laboratory information, molecular test outputs, and microbiological or genomic data in clinical microbiology.

Machine learning (ML). A major branch of AI in which algorithms learn relationships from data rather than relying only on fixed rules (Asnicar et al., 2024).

Quality control (QC). The activities that ensure laboratory procedures produce accurate and consistent results, including monitoring of culture media, reagents, microorganisms, testing procedures, and personnel performance.

Patient-based real-time quality control (PBRTQC). A quality monitoring approach in which patient-result distributions are analyzed to flag patterns that may indicate analytical shifts or errors; in this review, specifically machine-learning-supported PBRTQC (Lorde et al., 2024).

Total laboratory automation. Automated laboratory infrastructure that provides digital image capture and enables algorithm-assisted interpretation (Fischer et al., 2026).

Antimicrobial resistance (AMR). The ability of microorganisms to resist antimicrobial agents, which AI and ML models attempt to predict from genomic sequences, susceptibility data, and clinical information.

Descriptive review. A review design that summarizes and organizes existing published knowledge on a topic without conducting new experiments or collecting new patient data.

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METHODS

This section presents the research design, the sources of data, the data collection procedure, the method of data analysis, and the ethical considerations of the review.

Research Design

This study employed a descriptive review design to examine the applications of artificial intelligence in quality control practices in microbiology laboratories. The approach focused on reviewing and organizing published information about AI-assisted diagnostic procedures, laboratory quality monitoring, error detection, and automation.

The descriptive review design was selected because the study aimed to summarize existing knowledge and identify the potential contributions and limitations of AI, rather than conduct laboratory experiments or collect new patient data. The review was organized according to the conceptual framework presented in Figure 1, in which the reviewed literature served as the input, the extraction, grouping, and synthesis of information constituted the process, and the synthesized applications, benefits, challenges, and recommendations constituted the output.

Sources of Data

The primary source of information was the article by Dien Bard et al. (2025), entitled "Proceedings of the Clinical Microbiology Open 2024: Artificial Intelligence Applications in Clinical Microbiology," published in the Journal of Clinical Microbiology. This proceedings report served as the central reference for describing AI applications and broader considerations in clinical microbiology. It reports on the ClinMicro Open (CMO), an annual meeting organized by the American Society for Microbiology, whose 2024 edition was held in Oceanside, California, on February 1 and 2 under the theme "The Lab of the Future," with AI opportunities in clinical microbiology laboratories as one of its primary topics (Dien Bard et al., 2025).

Supplementary literature included the publications cited in the original manuscript and additional peer-reviewed studies relevant to the review objectives. These publications discussed AI-assisted bacterial growth monitoring (Jacot et al., 2024), interpretation of bacterial cultures and smears (Cintrón, 2025; Signoroni et al., 2023), and AI applications in microscopy and image analysis. Other sources examined patient-based real-time quality control and laboratory performance monitoring (Duan et al., 2024; Liang et al., 2024; Lorde et al., 2024; Su et al., 2026; Zhou et al., 2022), quantitative multiplex PCR automation (MacLean & Gunson, 2024), and AI applications in clinical laboratory practice (Hou et al., 2024).

The selected literature was reviewed and organized according to its relevance to the identified applications of AI in clinical microbiology. The discussion focused on diagnostic applications, laboratory quality control, workflow efficiency, potential benefits, and challenges associated with implementing AI-based technologies.

Data Collection Procedure

Information was gathered by reviewing the primary proceedings report and the supplementary publications identified in the manuscript. Relevant information was extracted and grouped according to the following themes: (1) AI applications in clinical microbiology; (2) image analysis, bacterial growth detection, and culture-plate interpretation; (3) AI-assisted microscopy and microorganism identification; (4) antimicrobial resistance analysis and prediction; (5) molecular diagnostic interpretation and automation; and (6) laboratory quality monitoring, error detection, benefits, and implementation challenges. The extracted information was organized according to the review objectives.

Data Analysis

A qualitative descriptive synthesis was used to summarize the information. Findings were organized by major AI application areas and interpreted in terms of their reported or potential contributions to clinical microbiology. Numerical findings were reported as presented in the original publications and were not recalculated or pooled. Because the sources differed in design, application, and purpose, their findings were described separately rather than treated as directly comparable. No inferential statistical analysis or meta-analysis was performed. The synthesized findings are presented narratively and in summary tables, and are interpreted in relation to the stages of the laboratory testing process and to the requirements for responsible implementation.

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Volume 1 Issue 4 Pages 4947-4963
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DOI: 10.5281/zenodo.24381589

Ethical Considerations

This review was based on published literature and did not involve human participants, identifiable patient records, or biological specimens. Accordingly, institutional ethical approval and informed consent were not required for this review. All sources were acknowledged through in-text citations and the reference list, and findings were reported as presented by the original authors.

RESULTS AND DISCUSSION

This section presents the findings of the review according to the major areas of AI application in clinical microbiology and laboratory quality control, followed by the benefits and challenges of implementation. Each set of findings is interpreted in relation to the reviewed literature.

The reviewed studies indicate that AI can improve laboratory workflow efficiency, reduce workload, and enhance quality and accuracy. It also helps strengthen quality control processes and offers more reliable testing. The reviewed literature describes AI applications across several areas of clinical microbiology. These include digital image analysis, bacterial growth detection, culture-plate interpretation, microscopy, molecular diagnostic interpretation, antimicrobial resistance prediction, and patient-based quality monitoring. The sources differ in design and scope; therefore, their findings are interpreted according to the type of evidence each publication provides. The primary source, Dien Bard et al. (2025), provides a central overview of AI applications in clinical microbiology, while the supplementary literature offers more focused examples of specific technologies and approaches. Table 1 summarizes the applications and their potential contributions to microbiological practice.

Applications of AI in Microbiology Laboratory Quality Control

AI technologies can support different microbiological procedures by improving reliability, assisting interpretation, and identifying unusual findings that require further investigation. Across the reviewed literature, the contribution of AI to quality control takes three broad forms: standardizing the interpretation of images and test outputs, flagging unusual results or performance patterns for review, and reducing repetitive manual work so that trained personnel can focus on questionable or complex findings.

Table 1. Applications of AI and Its QC Contributions

Laboratory procedure	Application of AI	QC contribution
Bacterial culture examination	Automated colony recognition	Supports consistent colony interpretation
Gram staining	Automated microscopic image analysis	Assists in standardized interpretation
Parasite examination	Automated parasite detection	Supports identification and reduces repetitive manual examination
Antimicrobial susceptibility testing	Analysis of susceptibility patterns	Helps identify unusual resistance results
Molecular diagnostics	Automated PCR result interpretation	Supports consistent interpretation and verification
Laboratory performance monitoring	Machine-learning algorithms	Helps detect possible errors and deviations

Table 1 shows that the applications reviewed span the main working areas of the microbiology laboratory, from culture and staining to susceptibility and molecular testing and to performance monitoring. Dien Bard et al. (2025), Jacot et al. (2024), and Signoroni et al. (2023) described several of these applications as emerging opportunities for clinical microbiology laboratories. Lorde et al. (2024) further clarified that machine learning can strengthen real-time quality control by helping identify systematic and non-systematic errors in clinical laboratory testing.

Summary of Key Studies Reviewed

Table 2 summarizes the principal studies discussed in this review and the focus or details reported for each, as presented by the original authors. The studies differ in design, setting, and purpose and are therefore described side by side rather than compared or pooled.

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ISSN: 3155-7546 (Online)
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Table 2. Summary of Key Studies Reviewed and Their Reported Focus

Source	Application area	Reported focus and details
Dien Bard et al. (2025)	Overview of AI applications	Proceedings report of ClinMicro Open 2024 (theme: "The Lab of the Future"); discusses AI opportunities in clinical microbiology, including colony identification, Gram-stain interpretation, parasite identification, resistance prediction, and process automation.
Jacot et al. (2024).	Bacterial growth monitoring	Algorithm for growth detection from any type of specimen on the most common media; 3,844 plates imaged 15 times and read independently by two microbiologists (99,944 human ground truths); performance evaluated at 18–24 h, at 48 h, and at earlier time points.
Signoroni et al. (2023).	Culture-plate interpretation	Hierarchical, multi-network AI (DeepColony) for global interpretation of culture plates, including presumptive pathogen identification, evaluated on urinary specimens and a set of 32 pathogens.
DeYoung et al. (2022).	Interpretive culture-plate reading	"Behind the scenes" considerations for AI in routine laboratories, including clearly defined intended use and representative data.
Lorde et al. (2024).	Patient-based real-time QC	Review of machine learning for PBRTQC and for analytical and pre-analytical error detection in the clinical laboratory.
Dong et al. (2024).	AI-based PBRTQC	Comparison of an AI-based PBRTQC model with a traditional PBRTQC model in identifying quality risks.
MacLean & Gunson (2024).	Molecular diagnostics	PCR.Ai as the final interpretation and verification step for in-house multiplex quantitative PCR for CMV, EBV, and adenovirus; 1,350 interpretations; 100% agreement with manual interpretation; about 63 minutes saved per run.
Alouani et al. (2021)	SARS-CoV-2 real-time PCR	Deep-learning analysis to improve the specificity of SARS-CoV-2 real-time PCR.
Gerada et al. (2024).	Antimicrobial susceptibility testing	Machine-learning-assisted agar dilution for determining minimum inhibitory concentrations.
Tejeda et al. (2024).	Antibiotic therapy selection	Retrospective validation of machine-learning software generating empirical and organism-targeted antibiotic recommendations from historical antibiogram data.
Ardila et al. (2024)	Resistance prediction	Systematic review of integrating whole-genome sequencing and machine learning to predict antimicrobial resistance in critical pathogens.
Işıl et al. (2025)	Virtual Gram staining	Virtual Gram staining of label-free bacteria using dark-field microscopy and deep learning.

As Table 2 illustrates, the evidence base ranges from a meeting report to technical development and validation studies to narrative and systematic reviews. This diversity is a strength in showing how widely AI is being explored, but it also means that the reported performance of one tool in one setting cannot simply be generalized to another, a point that recurs throughout the literature and is taken up in the discussion that follows.

AI in Bacterial Growth Detection and Culture Plate Interpretation

Jacot et al. (2024) developed and evaluated an AI-based algorithm for bacterial growth monitoring in clinical bacteriology using 3,844 culture plates. The plates were imaged repeatedly, and two microbiologists read the images independently to create the human reference against which the algorithm was assessed. The summary reports that the algorithm was evaluated over 48 hours, and also at earlier time points toward an early growth monitoring system, and achieved high sensitivity and specificity in distinguishing bacterial growth from no

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Volume 1 Issue 4 Pages 4947-4963
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growth. The authors noted that by 6 hours, about half of the positive plates already showed some growth, and envisioned automated early monitoring of normally sterile samples as a way for microbiologists to prioritize reading and to communicate early detection of growth to clinicians. This application may help optimize routine plate-reading processes and identify specimens that require attention. The study also emphasizes the importance of validation and expert oversight after implementation.

Signoroni et al. (2023) examined hierarchical AI for global interpretation of culture plates in digital microbiology and described its potential to recognize growth patterns and presumptive pathogens. Their system, DeepColony, combines several levels of image analysis with a final rule-based decision stage, and was developed for urinary specimens covering 32 pathogens, an approach that mirrors the staged reasoning of a microbiologist reading a plate (Signoroni et al., 2023). DeYoung et al. (2022) emphasized that algorithm development must begin with a clearly defined intended use and representative data. These considerations are important because colony appearance can vary with culture media, organism mixtures, incubation conditions, and image quality. Accordingly, AI-generated interpretations should be locally evaluated, and uncertain or atypical findings should be referred to trained personnel for review.

AI-assisted image analysis is relevant to microbiology because culture and microscopy procedures rely heavily on visual recognition. Automated colony recognition, digital plate interpretation, Gram-stain image analysis, and parasite detection may help reduce repetitive work and support consistency. The studies by Smith et al. (2018), DeYoung et al. (2022), Chin et al. (2024), Desruisseaux et al. (2024), and McMahon et al. (2025) illustrate different approaches to image-based analysis. Işıl et al. (2025) further demonstrated a virtual Gram-staining method using deep learning. However, model performance may vary with image quality, staining conditions, culture media, specimen type, organism diversity, and the datasets used for training. Laboratories should evaluate these systems under their own conditions and define when manual confirmation is required.

From a quality control standpoint, the value of image-based AI lies less in replacing the reader than in making the reading process more consistent and better prioritized. A tool that reliably separates no-growth plates from plates needing attention can free personnel time, while a tool that applies the same criteria to every image may reduce variation between readers. These benefits are conditional on the validation and oversight emphasized by the sources above, since an algorithm that performs well on the plates and media on which it was developed may perform differently on a laboratory's own specimens.

AI in Laboratory Quality Monitoring and Error Detection

One important application of AI is its potential to detect laboratory errors and unusual testing patterns. Traditional QC procedures commonly involve monitoring control results and reviewing laboratory records. Machine learning may provide additional support by analyzing patient-based data and identifying unexpected changes in laboratory performance.

Lorde et al. (2024) discussed how machine learning can be integrated into patient-based real-time quality control to improve the detection of analytical and pre-analytical errors. This application may help laboratories identify possible problems earlier and initiate appropriate investigations and corrective actions.

Duan et al. (2024) discussed next-generation patient-based quality control systems, emphasizing continuous laboratory performance monitoring and early error detection. Zhou et al. (2022) investigated machine learning for real-time quality control using patient data, while Dong et al. (2024) compared an AI-based PBRTQC model with a traditional model for identifying quality risks. These approaches suggest that machine learning may improve detection of selected patterns or shifts, but performance depends on analyte characteristics, patient population, instrument behavior, and appropriate model configuration.

AI may also strengthen quality monitoring by identifying unusual patterns in patient-based data. The publications by Lorde et al. (2024), Duan et al. (2024), Zhou et al. (2022), and Liang et al. (2024) discuss approaches to patient-based real-time QC and ML-based monitoring. These methods may complement conventional controls by providing another way to detect deviations or possible errors. They should not, however, replace established QC materials, calibration, maintenance, proficiency testing, or other required quality management activities. The laboratory must define how it assesses, investigates, documents, and links alerts to corrective action. Excessive false alerts may disrupt work, while missed errors may create a false sense of security.

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Volume 1 Issue 4 Pages 4947-4963
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DOI: 10.5281/zenodo.24381589

AI in Molecular Diagnostic Quality Control

AI may also support quality control in molecular diagnostics, particularly in PCR-based testing. MacLean and Gunson (2024) evaluated AI as an automated interpretation and verification tool for quantitative multiplex PCR testing involving cytomegalovirus (CMV), Epstein–Barr virus (EBV), and adenovirus in blood samples. The system, PCR.Ai, was used as the final interpretation and verification step for routine in-house tests. Their study evaluated 1,350 interpretations and reported 100% agreement between the AI-assisted system and the established manual interpretation method. The authors also reported a saving of approximately 63 minutes per run. However, this finding reflects a single assay and laboratory setting, so similar results would still need to be demonstrated in other institutions. Alouani et al. (2021) demonstrated that deep-learning analysis could improve the specificity of SARS-CoV-2 real-time PCR interpretation, while Alouani et al. (2022) explored convolutional neural networks for urine-culture analysis. These examples show how algorithmic interpretation may support defined diagnostic workflows, although each application requires assay-specific evaluation.

These findings show how automated interpretation may support consistency and reduce manual review time in a defined molecular testing workflow. The reported agreement applies to the assay and laboratory conditions evaluated in that study. It does not establish equivalent performance for all PCR platforms, targets, or laboratories; local verification and ongoing monitoring remain necessary. Molecular diagnostic applications thus provide another example of AI-assisted interpretation. Alouani et al. (2021) used deep learning to improve the specificity of SARS-CoV-2 real-time PCR analysis, and MacLean and Gunson (2024) reported high agreement between AI-assisted and manual interpretation in a defined multiplex PCR workflow. These findings suggest that AI may help standardize interpretation and reduce review time for selected assays. Nevertheless, a result from one assay or laboratory cannot establish equivalent performance across other platforms, targets, and patient populations.

AI in Antimicrobial Resistance Analysis and Prediction

AI has potential applications in analyzing antimicrobial resistance patterns and predicting bacterial resistance. Li et al. (2024) reviewed the use of AI and machine learning in predicting antimicrobial resistance among pathogenic microorganisms. These technologies may help researchers and laboratory professionals analyze complex microbiological and genomic information.

Ardila et al. (2024) examined the integration of whole-genome sequencing and machine learning for resistance prediction, while Bilal et al. (2025) summarized the broader role of AI and ML in AMR prediction and surveillance. These approaches can analyze complex genomic, phenotypic, and epidemiological information, but their predictions must be interpreted in relation to the quality and representativeness of the underlying data.

Machine-learning methods have also been investigated in antimicrobial susceptibility testing. Gerada et al. (2024) described machine-learning-assisted agar dilution for determining minimum inhibitory concentrations. This approach may support the analysis of susceptibility results, but conventional susceptibility testing and appropriate reference standards remain essential for confirmation.

Machine learning has also been evaluated as a decision-support approach for antimicrobial therapy. Tejeda et al. (2024) retrospectively assessed software that generated empirical and organism-targeted antibiotic recommendations using historical antibiogram data. Such tools may contribute to antimicrobial stewardship, but their recommendations require validation against local resistance patterns, current guidelines, and patient-specific clinical information.

In clinical microbiology, such applications may support antimicrobial resistance surveillance and deliver information for antimicrobial stewardship programs. AI applications in AMR analysis are promising because resistance prediction may draw on genomic sequences, susceptibility results, and clinical information. Reviews by Ardila et al. (2024) and Bilal et al. (2025), along with the study by Gerada et al. (2024), show that machine-learning methods are being investigated for resistance prediction and minimum inhibitory concentration determination. However, model predictions are influenced by the organisms represented in the training data, the distribution of resistance phenotypes, laboratory methods, and changes in local epidemiology. AI-generated predictions should support, not replace, validated antimicrobial susceptibility testing and expert interpretation.

Benefits and Challenges of AI Implementation

The literature identifies potential benefits and practical challenges associated with AI implementation in microbiology laboratories. The main themes identified in the reviewed sources are presented in Table 3.

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Volume 1 Issue 4 Pages 4947-4963
ISSN: 3155-7546 (Online)
DOI: 10.5281/zenodo.24381589

Table 3. Potential Benefits and Challenges of AI Implementation in Microbiology Laboratories

Potential benefits	Challenges
Improved laboratory workflow and reduced repetitive manual tasks	High initial and continuing implementation costs
More consistent interpretation of selected images and test outputs	Incomplete, unrepresentative, or poor-quality data
Earlier identification of unusual results or performance patterns	Need for local verification, validation, and ongoing monitoring
Additional support for quality monitoring and error detection	Limited availability of personnel with technical expertise
Support for antimicrobial resistance surveillance	Data privacy, cybersecurity, and governance requirements
Potential reduction in manual review time for defined workflows	Regulatory, ethical, and accountability considerations

The benefits and challenges in Table 3 are closely linked. The same features that make AI attractive, such as consistency, speed, and the ability to process large volumes of images or results, also create dependencies on data quality, technical expertise, and sustained resources. For example, the workflow gains reported for plate reading and PCR interpretation depend on algorithms that were developed and validated on representative data, which in turn requires the data quality, expertise, and funding listed among the challenges. Overall, the literature indicates that AI may strengthen laboratory quality control, but successful implementation requires appropriate validation, personnel training, and continuous monitoring. The findings suggest that artificial intelligence has the potential to improve quality control practices in microbiology laboratories, with applications that extend across diagnostic interpretation, workflow efficiency, and laboratory quality monitoring.

Interpreting AI Applications Across the Laboratory Testing Process

Because laboratory quality depends on the pre-analytical, analytical, and post-analytical phases, the reviewed applications can be interpreted in terms of where in the testing process they contribute. Patient-based real-time quality control has been discussed for detecting both analytical and pre-analytical errors (Lorde et al., 2024), which positions it as a surveillance layer that operates across phases. Image-based culture and microscopy interpretation, molecular result interpretation, and susceptibility analysis act chiefly at the analytical stage and at the point where results are verified (DeYoung et al., 2022; Jacot et al., 2024; MacLean & Gunson, 2024; Signoroni et al., 2023). Resistance prediction and antibiotic recommendation tools extend into the post-analytical phase, where results are interpreted for surveillance and stewardship (Bilal et al., 2025; Tejeda et al., 2024). This mapping is the interpretation of this review, not a classification reported by the original authors, but it illustrates why AI cannot be treated as a single quality tool: each application addresses a different kind of risk and requires its own evaluation.

AI-assisted image analysis and molecular interpretation can also be seen as ways to standardize steps that are otherwise subjective or repetitive. Culture-plate reading, Gram-stain interpretation, and review of amplification curves all depend on trained judgment, and differences in judgment between readers or over time are a recognized source of variation. By applying consistent criteria, AI-assisted tools may narrow such variation, as suggested by the agreement reported between AI-assisted and manual interpretation in a defined multiplex PCR workflow (MacLean & Gunson, 2024). The review nonetheless stresses that consistency is not the same as correctness: a consistent but poorly validated algorithm would reproduce its errors consistently.

Human Oversight, Validation, and Accountability

A consistent message across the reviewed sources is that AI-generated outputs remain subject to professional review. Jacot et al. (2024) emphasized validation and expert oversight after implementation, DeYoung et al. (2022) emphasized defined intended use and representative data, and Fischer et al. (2026) discussed the need for integrated internal quality control in automated workflows. Together, these positions imply that an AI tool should be treated like any other critical element of the testing process: its intended use should be defined, its performance verified locally, its behavior monitored over time, and its outputs reviewed by competent personnel, with uncertain or atypical findings referred for expert interpretation.

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Volume 1 Issue 4 Pages 4947-4963
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Accountability also deserves explicit attention. Although AI may assist interpretation, responsibility for the final result remains with the laboratory and its professionals. Laboratories therefore need clear procedures defining who reviews AI outputs, how disagreements between the tool and the reader are resolved, how alerts are investigated and documented, and how software updates or changes in instruments and reagents are assessed for their effect on performance. Without such procedures, excessive false alerts may disrupt work and missed errors may create a false sense of security.

Table 4. Implementation Considerations Drawn from the Reviewed Literature

Consideration	Description	Basis
Define intended use and data	Begin with a clearly defined intended use and representative data, since colony appearance varies with media, organism mixtures, incubation conditions, and image quality.	DeYoung et al. (2022)
Verify and validate locally	Evaluate AI outputs under the laboratory's own conditions before routine use; results from one assay or laboratory do not establish equivalent performance elsewhere.	Jacot et al. (2024); MacLean & Gunson (2024)
Integrate within a quality framework	Coordinate instruments, software, consumables, and reagents that often come from different manufacturers; verify system performance, identify software or instrument changes, and document deviations.	Fischer et al. (2026)
Monitor performance continuously	Assess system performance, identify errors, and evaluate the effects of software updates or changes in operating conditions.	Synthesis of this review
Retain professional review	Refer uncertain or atypical findings to trained personnel, who retain responsibility for final decisions.	Jacot et al. (2024); DeYoung et al. (2022)
Establish governance	Adopt policies on data privacy, cybersecurity, documentation, and accountability.	Synthesis of this review

Relevance to Laboratories in the Philippines and Other Resource-Limited Settings

The cost, expertise, and infrastructure challenges identified in Table 3 are likely to weigh most heavily in resource-limited settings. Because the benefits of automation depend on integrating instruments, software, consumables, and quality monitoring processes (Fischer et al., 2026), adoption involves ongoing, not only initial, costs and requires reliable infrastructure, technical support, and trained personnel. For laboratories in the Philippines and other resource-limited settings, adoption should therefore be guided by the availability of these resources and by sustainable funding. A phased approach may be more practical than immediate investment in full automation. Laboratories can begin by evaluating a specific application, such as digital image triage or quality-monitoring software, and assess its value before expanding its use. The reviewed sources were not specific to the Philippines; this discussion applies their general requirements to that context.

Limitations of the Review

This review has limitations. It used a descriptive review design and relied primarily on the proceedings report by Dien Bard et al. (2025), together with supplementary publications identified in the original manuscript. It was not a systematic review; it did not include a comprehensive database search strategy, formal critical appraisal, or risk-of-bias assessment. The included publications also differ in design, application, and outcome measures, which limits direct comparison. In addition, several reported performance figures come from single studies conducted in particular laboratories and settings. Accordingly, the review describes potential applications and implementation considerations rather than establishing the overall effectiveness of AI across microbiology laboratories.

CONCLUSIONS AND RECOMMENDATIONS

Summary of Findings

The review of the literature on AI in clinical microbiology and laboratory quality control yielded the following findings:

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Volume 1 Issue 4 Pages 4947-4963
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1. AI applications have been reported across the main working areas of the microbiology laboratory, including colony recognition and culture-plate interpretation, Gram-stain and parasite image analysis, antimicrobial susceptibility and resistance prediction, molecular result interpretation, and patient-based real-time quality monitoring.
2. The potential benefits include improved workflow, reduced repetitive manual tasks, more consistent interpretation of selected images and test outputs, earlier identification of unusual results or performance patterns, support for quality monitoring and resistance surveillance, and possible reductions in manual review time for defined workflows.
3. The main challenges are high initial and continuing implementation costs, incomplete or poor-quality data, the need for local verification and ongoing monitoring, limited technical expertise, data privacy and governance requirements, and regulatory, ethical, and accountability considerations.
4. Reported performance, such as the agreement between AI-assisted and manual interpretation in a multiplex PCR workflow, applies to the specific assays and laboratory conditions studied and does not establish equivalent performance elsewhere.

Conclusions

AI can improve clinical microbiology practices through automated image analysis, bacterial culture interpretation, molecular diagnostic analysis, antimicrobial resistance prediction, and laboratory error detection. The reviewed literature demonstrates that AI-assisted systems can support diagnostic interpretation, improve workflow efficiency, and strengthen laboratory quality monitoring. However, their reliability depends on appropriate validation, data quality, continuous performance monitoring, and professional oversight. AI should therefore serve as a complementary tool rather than a replacement for established laboratory procedures and the expertise of microbiology professionals.

Because the evidence reviewed is descriptive and drawn from studies of differing design and setting, these conclusions concern the potential contributions and implementation requirements of AI, not its proven overall effectiveness across microbiology laboratories. The responsible use of AI in clinical microbiology depends on treating it as part of the laboratory's quality system, subject to the same standards of verification, monitoring, documentation, and accountability as other critical components of testing.

Recommendations

To translate the findings and conclusions of this review into practice, the following recommendations are offered for laboratories, laboratory personnel, institutions, and researchers.

1. Needs-Based and Phased Adoption

Microbiology laboratories should identify specific diagnostic or quality control needs before adopting AI technologies and evaluate their suitability, cost, and compatibility with existing procedures. In the Philippines and other resource-limited settings, adoption should be guided by the availability of reliable infrastructure, technical support, trained personnel, and sustainable funding. A phased approach, beginning with a specific application such as digital image triage or quality-monitoring software, is more practical than immediate investment in full automation.

2. Local Verification, Validation, and Continuous Monitoring

AI applications should undergo appropriate local verification or validation using representative laboratory data before routine use. Continuous monitoring should also be established to assess system performance, identify errors, and evaluate the effects of software updates or changes in operating conditions.

3. Training and Professional Oversight

Laboratory personnel should receive adequate training on the capabilities and limitations of AI-assisted systems while retaining responsibility for reviewing questionable results and making final professional decisions. Laboratories should define when manual confirmation is required.

4. Governance, Data Protection, and Accountability

Laboratories and their institutions should establish policies addressing data privacy, cybersecurity, documentation, and accountability, including procedures for investigating and documenting alerts and linking them to corrective action.

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5. Integration with the Existing Quality System

AI-based monitoring and interpretation tools should complement, and not replace, internal quality control materials, calibration, maintenance, proficiency testing, and other established quality management activities, and should be coordinated with the laboratory's instruments, software, and reagents.

6. Future Research

Future research should assess the performance, reproducibility, practical benefits, and cost-effectiveness of AI applications across different laboratory settings, particularly in resource-limited institutions. Systematic reviews with comprehensive search strategies and formal appraisal would further strengthen the evidence base. These efforts can help ensure that AI is implemented responsibly and contributes meaningfully to the advancement of clinical microbiology.

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Volume 1 Issue 4 Pages 4947-4963
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