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Artificial Intelligence Preparedness and Perceived Challenges in Soil-Transmitted Helminth Identification among Medical Technologists in Metro Manila

Marielle Jane R. Fernandez, Fatima Zahra H. Balahim, Princess Emerald S. Catipay, Francis Philip Y. Dacillo, Geraldine T. Dela Cruz, Jheammy R. Eustaquio,, Jeaneil P. Zerrudo, and Dr. Leah F. Quinto

Abstract

Artificial intelligence-assisted microscopy may improve the efficiency and consistency of soil-transmitted helminth identification, but its implementation depends on workforce preparedness and institutional capacity. This study assessed preparedness and perceived challenges related to artificial intelligence integration among registered medical technologists working in secondary and tertiary hospitals in Metro Manila. A cross-sectional descriptive-comparative survey was conducted among 100 respondents using a validated researcher-developed questionnaire. Frequencies, percentages, means, and standard deviations were used for descriptive analysis. Kruskal-Wallis H and Mann-Whitney U tests examined differences according to age, professional experience, and the availability of institutional artificial intelligence seminars or workshops, with a Bonferroni-adjusted alpha of .017. Overall preparedness was moderate (M = 2.61, SD = 0.51). Willingness to learn artificial intelligence-based diagnostic tools was high (M = 3.05), whereas perceived laboratory readiness was low (M = 2.15). Perceived challenges were high overall (M = 3.22, SD = 0.39). Financial constraints were rated very high (M = 3.44), while inadequate infrastructure (M = 3.10) and limited educational opportunities (M = 3.06) were rated high. No statistically significant differences were detected across the tested respondent characteristics. The findings indicate that medical technologists are receptive to artificial intelligence, but institutional financing, structured training, reliable infrastructure, and professional oversight are necessary before AI-assisted parasitology can be implemented responsibly.

Keywords: *artificial intelligence; clinical laboratory readiness; medical technologists; parasitological diagnosis; soil-transmitted helminths; technology adoption*

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1. Introduction

Artificial intelligence (AI) is increasingly being incorporated into healthcare to support diagnostic interpretation, automate repetitive procedures, improve workflow efficiency, and reduce variability associated with manual examination. In laboratory medicine, these applications include automated image analysis, pattern recognition, digital microscopy, and decision-support systems. Their relevance is particularly evident in diagnostic procedures that depend heavily on visual recognition and operator expertise. AI-assisted microscopy may therefore provide an important supplementary approach in parasitology, where accurate identification commonly relies on the ability of trained laboratory professionals to recognize parasite morphology in clinical specimens (Oduoye et al., 2024; Parija & Poddar, 2024).

Soil-transmitted helminth infections remain an important public health concern, particularly in low- and middle-income countries. The principal soil-transmitted helminths affecting humans include *Ascaris lumbricoides*, *Trichuris trichiura*, and hookworms. These infections are associated with nutritional deficiencies, anemia, impaired physical development, reduced cognitive performance, and diminished quality of life, especially among children and other vulnerable populations (World Health Organization, 2023). In the Philippines, soil-transmitted helminthiasis continues to persist despite long-standing deworming, sanitation, and health-education programs, indicating the continuing need for reliable surveillance and diagnostic systems (Mationg et al., 2021).

Conventional diagnosis of soil-transmitted helminth infections remains largely dependent on microscopic examination. Techniques such as Kato-Katz and concentration procedures are practical and widely used, but their performance may be affected by specimen quality, infection intensity, observer competence, workload, and variability in morphological interpretation. Their sensitivity may also decrease in low-intensity infections, which can undermine prevalence estimation and disease-monitoring efforts (Grau-Pujol et al., 2021; Miswan et al., 2022). These limitations have encouraged the development of optical, molecular, and digital approaches intended to improve diagnostic consistency and sensitivity (Meulah et al., 2023).

Recent advances in digital microscopy and deep-learning image analysis have demonstrated the technical feasibility of automated or AI-supported helminth detection. AI-based systems have been developed to identify and quantify parasite eggs in stool-smear images, reduce the time required for manual screening, and support diagnostic work in settings where experienced microscopists are limited. Proof-of-concept and field studies have shown that digital platforms can be adapted for neglected tropical disease diagnostics and deployed in resource-constrained environments (Lundin et al., 2024; Ward et al., 2022). Similar developments have been reported in systems designed to classify soil-transmitted helminth eggs and support standardized interpretation of digital microscopic images (Cure-Bolt et al., 2024; Lee et al., 2022; Xu et al., 2024).

The successful adoption of these technologies, however, cannot be determined by diagnostic performance alone. AI implementation requires compatible laboratory equipment, reliable electricity and internet connectivity, technical maintenance, data-governance mechanisms, institutional financing, and personnel who are adequately prepared to use and evaluate AI-generated results. The integration of AI into laboratory medicine also raises questions concerning professional accountability, data privacy, system reliability, validation, and the continued role of human judgment in diagnostic decision-making (Oduoye et al., 2024; Sarmiento et al., 2025). AI is therefore more appropriately viewed as a potential complement to medical technologists rather than a substitute for their professional competence.

In the Philippine healthcare context, AI adoption remains uneven. Although healthcare institutions increasingly recognize the potential of digital technologies, readiness differs according to institutional resources, infrastructure, governance, and access to professional training. Financial constraints may prevent laboratories from acquiring digital microscopes, licensed software, data-storage capacity, and technical support. Inadequate training opportunities may also limit the ability of medical technologists to understand AI outputs, recognize algorithmic limitations, and incorporate automated systems into routine diagnostic workflows. These concerns are particularly important in parasitology, where AI-supported identification remains an emerging practice rather than a standard component of clinical laboratory operations.

Medical technologists occupy a central position in the implementation of AI-assisted parasitological diagnostics. They are responsible for specimen processing, microscopic examination, quality assurance, result verification, and the interpretation of laboratory findings within established clinical procedures. Their willingness to learn, perception of institutional readiness, and awareness of implementation barriers may influence whether AI systems are accepted and appropriately used. Preparedness must therefore be considered at both individual and institutional levels. A workforce may be open to learning about AI while remaining unable to use it because the laboratory lacks the necessary equipment, training, technical support, or administrative commitment.

Existing studies have primarily concentrated on the technical accuracy of AI-supported parasite identification, the development of digital microscopy platforms, or the general implications of AI adoption in healthcare. Comparatively less attention has been given to the preparedness of registered medical technologists who would be expected to use these technologies in routine laboratory settings. Evidence is especially limited in the Philippine context and in relation to soil-transmitted helminth identification. Assessing the perspectives of medical technologists can therefore provide an institutional and workforce-level complement to the growing technical literature on AI-assisted parasitology.

Metro Manila provides a relevant setting for such an assessment because its secondary and tertiary hospitals manage substantial diagnostic workloads and may encounter differing levels of digital laboratory capacity. Hospital classification alone does not guarantee readiness for AI adoption. Differences in budget allocation, laboratory infrastructure, staff development, technical support, and organizational priorities may continue to constrain implementation. Examining preparedness and perceived challenges across these institutions can help identify conditions that must be addressed before AI-assisted soil-transmitted helminth identification can be responsibly incorporated into clinical practice.

This study aimed to assess preparedness and perceived challenges associated with the integration of artificial intelligence into soil-transmitted helminth identification among registered medical technologists in Metro Manila. Specifically, it sought to: (1) describe the respondents according to age, years of professional experience, availability of institution-sponsored AI seminars or workshops, and hospital classification; (2) determine their level of preparedness for AI integration in soil-transmitted helminth identification; (3) assess perceived challenges related to financial resources, limited educational opportunities, and inadequate infrastructure; and (4) determine whether preparedness and perceived challenge scores differed according to age, years of professional experience, and the availability of institution-sponsored AI seminars or workshops.

2. Review of Related Literature

2.1 Soil-Transmitted Helminthiasis and Limitations of Conventional Diagnosis

Soil-transmitted helminthiasis remains a persistent public health problem in low- and middle-income countries, particularly where sanitation, environmental hygiene, and access to diagnostic services remain inadequate. The major human soil-transmitted helminths include *Ascaris lumbricoides*, *Trichuris trichiura*, and hookworm species. These infections may contribute to anemia, malnutrition, impaired growth, reduced cognitive development, and diminished quality of life, especially among children and other vulnerable populations (World Health Organization, 2023). In the Philippines, continued transmission has been documented despite long-standing school-based deworming and health-education programs, indicating that surveillance, diagnosis, treatment, and prevention remain important components of control efforts (Mationg et al., 2021).

Conventional diagnosis continues to rely primarily on microscopic examination of stool specimens. The Kato-Katz technique and concentration procedures remain widely used because they are relatively affordable, practical, and suitable for routine or population-based examination. Nevertheless, their diagnostic performance is influenced by infection intensity, specimen preparation, observer competence, and the number of samples or slides examined. Microscopy may have reduced sensitivity in low-intensity infections, which becomes increasingly important as control programs lower parasite burdens and move toward transmission interruption (Grau-Pujol et al., 2021; Miswan et al., 2022).

Advances in molecular and optical technologies have consequently been explored to improve diagnostic sensitivity and standardization. Polymerase chain reaction-based approaches can detect low-intensity infections more sensitively than conventional microscopy, although they require specialized equipment, technical expertise, and financial resources (Grau-Pujol et al., 2021). Innovative optical devices and digital microscopy systems likewise seek to improve image quality, documentation, portability, and automated interpretation (Meulah et al., 2023). These developments demonstrate that conventional microscopy remains indispensable but may be strengthened through complementary technologies that reduce observer variability and improve the detection of low-burden infections.

2.2 Artificial Intelligence and Digital Microscopy in Parasitological Diagnosis

Artificial intelligence has expanded the capabilities of digital microscopy by enabling automated image classification, object detection, parasite counting, and pattern recognition. In parasitology, AI-based systems are being developed to identify parasite eggs and other microscopic forms from digitized specimen images. These systems generally use machine-learning or deep-learning algorithms trained on annotated image datasets to distinguish parasite morphology from artifacts and background material. Their potential contribution lies in reducing repetitive manual screening, standardizing interpretation, and supporting laboratories where experienced microscopists are limited (De Niz et al., 2026; Parija & Poddar, 2024).

Several studies have demonstrated the technical feasibility of AI-assisted helminth identification. Lee et al. (2022) developed the Helminth Egg Analysis Platform, which integrated deep-learning architectures for microscopic egg identification and quantification. Ward et al. (2022) presented an affordable AI-based digital pathology system for detecting soil-transmitted helminth and *Schistosoma mansoni* eggs in Kato-Katz thick smears. The study illustrated how digital image acquisition and automated analysis could be adapted to neglected tropical disease diagnostics without relying exclusively on high-cost laboratory systems.

Field-based applications have also shown that AI-assisted microscopy can be deployed in resource-constrained environments. Lundin et al. (2024) evaluated digital mobile microscopy combined with AI for diagnosing soil-transmitted helminth infections in Kenya. Cure-Bolt et al. (2024) similarly examined AI-based digital pathology for

detecting and quantifying helminth eggs. These studies are important because they move beyond algorithm development and consider the use of AI-supported systems under operational conditions.

Recent models have also addressed computational and technical limitations. Xu et al. (2024) developed a lightweight deep-learning model intended to reduce computational requirements while maintaining parasite-egg detection performance. Such approaches may be particularly relevant to laboratories that lack advanced computing infrastructure. Other studies have reported AI platforms capable of recognizing multiple helminth egg types and improving diagnostic efficiency through real-time or automated analysis (He et al., 2024; Zhu et al., 2024).

Despite these advances, technical performance may vary when AI systems encounter images, devices, specimen preparations, or parasite distributions that differ from their training data. Penpong et al. (2024) emphasized the out-of-domain problem in parasite-egg detection, demonstrating that systems performing well on controlled datasets may experience reduced accuracy under field conditions. Kumar et al. (2023) likewise identified challenges concerning image quality, scanning procedures, hardware requirements, dataset standardization, and integration into laboratory workflows. AI-supported parasitology should therefore be treated as an assistive diagnostic innovation requiring local validation, quality assurance, and professional oversight rather than as an autonomous replacement for laboratory expertise.

More broadly, patient-centered analytics scholarship emphasizes that computational outputs should supplement rather than displace contextual interpretation and professional judgment, with interpretability, ethical governance, and human review remaining essential when analytic systems influence healthcare decisions (Atento, Quinto, Espelita, & San Juan, 2025).

2.3 Healthcare Workforce Preparedness and Acceptance of Artificial Intelligence

The introduction of AI into healthcare depends not only on technological capability but also on the preparedness of the professionals expected to use it. Healthcare workers must understand the functions, limitations, and risks of AI systems before these tools can be responsibly incorporated into clinical decision-making. Preparedness includes awareness, willingness to learn, confidence in interpreting AI-supported outputs, access to training, and institutional support for implementation.

Studies of stakeholder perceptions generally show cautious acceptance of AI. Tursynbek et al. (2024) found that patients recognized the potential of AI to improve diagnostic efficiency and reduce medical errors but preferred that it remain under the supervision of healthcare professionals. Respondents also emphasized the continuing importance of empathy, communication, accountability, and trust. These findings support a complementary model in which AI assists healthcare professionals without displacing human judgment.

Comparable evidence from another professional domain shows that practitioners are more receptive to AI for assistive and preliminary functions than for autonomous decision-making, while deeper adoption remains conditional on management support, data readiness, policy institutionalization, and continued human verification (Bendal et al., 2026).

In the Philippine context, readiness is shaped by institutional, regulatory, and workforce conditions. Sarmiento et al. (2025) observed that AI could help address healthcare-worker shortages and unequal access to services, but its responsible use requires governance mechanisms, data protection, accountability, and safeguards against widening health inequalities. The authors noted that Philippine AI initiatives in healthcare remain relatively limited and concentrated in particular settings, indicating that technological interest has not yet translated into widespread implementation.

Broader analyses of the Philippine labor market similarly identify a gap between AI exposure and organizational readiness. Cucio and Hennig (2025) reported that AI presents opportunities for occupational complementarity but that skills, regulation, governance, and investment remain important constraints. Microsoft Philippines Communications Team (2024) also reported widespread use of AI among Filipino knowledge workers alongside concerns among organizational leaders regarding the absence of clear implementation strategies. Although these findings are not specific to clinical laboratories, they illustrate a broader pattern in which individual exposure to AI may develop more rapidly than formal institutional preparedness.

For medical technologists, preparedness requires more than familiarity with general-purpose AI tools. Laboratory implementation demands competence in digital microscopy, validation, quality control, data interpretation, workflow integration, troubleshooting, and recognition of algorithmic error. Medical technologists must also retain proficiency in manual diagnostic methods because AI-generated outputs require verification and because automated systems may

be disrupted by technical failures. Workforce readiness should therefore be viewed as a combination of personal receptiveness, professional competence, and institutional capacity rather than as simple awareness of AI.

Within healthcare, analytics capability has likewise been conceptualized as a socio-technical organizational resource involving tools, personnel, governance, interpretive capacity, and cross-functional alignment rather than technology acquisition alone (Atento, Quinto, Espelita, & Castaneda, 2025).

2.4 Financial, Educational, and Infrastructural Barriers to AI Adoption

AI adoption in laboratory medicine entails significant resource requirements. Digital microscopes, imaging devices, computers, software licenses, data-storage systems, cybersecurity controls, technical maintenance, and system validation may require substantial capital and recurring expenditure. These costs can be difficult to absorb in institutions whose budgets are already concentrated on routine operations, staffing, reagents, and essential patient services. Oduoye et al. (2024) noted that low- and middle-income countries face particular challenges in adopting AI in laboratory medicine because of resource limitations, inadequate infrastructure, shortages of trained personnel, and regulatory gaps.

Financial constraints are closely linked to infrastructure readiness. AI-supported diagnostic systems may depend on stable electricity, reliable internet connectivity, secure digital networks, compatible laboratory information systems, and technical personnel capable of maintaining hardware and software. Parija and Poddar (2024) emphasized that the limited availability of high-quality data and digital resources in endemic settings restricts the development and implementation of AI in parasitic disease control. Kenneth et al. (2024) similarly identified the absence of standardized, well-annotated datasets and limited interdisciplinary collaboration as barriers to the broader application of AI in intestinal-parasite diagnosis.

The technical integration of AI into existing laboratory workflows also presents practical difficulties. Kumar et al. (2023) described challenges associated with image-acquisition hardware, scanning methodologies, algorithm generalizability, and system scalability. Laboratories may need to redesign procedures for specimen imaging, result verification, data storage, and quality assurance. Even where an AI tool is affordable, implementation may fail if the institution lacks technical support or if the system cannot operate reliably under local conditions.

Educational limitations constitute an equally important barrier. General awareness of AI does not necessarily translate into applied competence. Medical technologists require structured training on image acquisition, interpretation of automated results, recognition of false-positive and false-negative outputs, data privacy, ethical use, and maintenance of manual diagnostic proficiency. Without continuing professional development, users may either over-rely on AI-generated results or reject potentially useful systems because of uncertainty and insufficient confidence.

Sarmiento et al. (2025) argued that responsible AI adoption in Philippine healthcare requires coordinated action involving policy, governance, workforce education, and infrastructure development. Cucio and Hennig (2025) likewise identified skills development and institutional capability as central to the Philippines' AI readiness. These findings indicate that financial, educational, and infrastructural barriers are interdependent. Limited funding constrains equipment acquisition and training, inadequate infrastructure reduces the usefulness of acquired systems, and insufficient education weakens the capacity of personnel to implement the technology safely.

Comparable institutional research has found that users may recognize AI's benefits while still identifying access, cost, privacy, algorithmic bias, and limited training or technical support as systemic constraints on deeper adoption (Rao et al., 2025).

Evidence from Philippine manufacturing organizations further indicates that infrastructure capability and data-privacy practices are positively interrelated, illustrating why system scalability, security, compliance, and governance readiness should be developed together (Somono & Generoso, 2026).

2.5 Synthesis and Research Gap

The reviewed literature demonstrates that soil-transmitted helminthiasis remains a significant diagnostic and public health concern, while conventional microscopy continues to face limitations in sensitivity, consistency, and dependence on trained observers (Grau-Pujol et al., 2021; Mationg et al., 2021; Miswan et al., 2022). AI-assisted digital microscopy offers a promising complementary approach, with several studies demonstrating the feasibility of automated helminth-egg detection, quantification, and classification in experimental and resource-constrained settings (Cure-Bolt et al., 2024; Lee et al., 2022; Lundin et al., 2024; Ward et al., 2022).

However, technical feasibility does not ensure successful implementation. AI systems require appropriate datasets, validated algorithms, suitable hardware, reliable infrastructure, technical support, and integration into existing laboratory procedures (Kumar et al., 2023; Penpong et al., 2024). Their adoption also depends on the preparedness of healthcare professionals and the institutional environment in which they work. Philippine literature suggests that interest in AI is increasing, but policy, training, infrastructure, governance, and financial limitations continue to constrain responsible adoption (Cucio & Hennig, 2025; Sarmiento et al., 2025).

From a broader health-workforce perspective, professional supply and qualification do not necessarily establish operational readiness when emerging service requirements are not matched by competency-development systems, institutional investment, and coordinated training ecosystems (Atento, Quinto, & Espelita, 2025).

Most available studies emphasize algorithm development, diagnostic accuracy, digital microscopy platforms, or general AI readiness in healthcare and the broader workforce. Comparatively limited evidence addresses the perspectives of registered medical technologists who may eventually operate, verify, and integrate AI-assisted systems in routine parasitology. Evidence is particularly limited concerning their preparedness for AI-supported soil-transmitted helminth identification and the financial, educational, and infrastructural challenges associated with its implementation in Philippine hospitals.

The present study addresses this gap by examining individual and institutional dimensions of AI readiness among registered medical technologists working in secondary and tertiary hospitals in Metro Manila. By assessing preparedness together with implementation barriers, the study contributes workforce-level evidence that complements the predominantly technical literature on AI-assisted parasitological diagnosis.

3. Methodology

3.1 Research Design

The study employed a quantitative, cross-sectional descriptive-comparative survey design to assess preparedness and perceived challenges associated with integrating artificial intelligence into soil-transmitted helminth identification. The descriptive component characterized the respondents and summarized preparedness and challenge scores. The comparative component examined whether these scores differed according to selected demographic and AI-related characteristics.

3.2 Participants and Study Setting

The study included 100 registered medical technologists employed in secondary and tertiary hospitals in Metro Manila. Of the respondents, 58 worked in tertiary hospitals and 42 worked in secondary hospitals. Eligible participants were licensed medical technologists between 23 and 60 years of age who had at least six months of clinical laboratory experience and academic or professional exposure to parasitology or clinical microscopy. Medical technology interns, nonlicensed laboratory personnel, individuals working outside Metro Manila, and respondents who did not provide informed consent were excluded.

3.3 Sampling Technique

Purposive sampling was used to recruit registered medical technologists who satisfied the eligibility criteria. Hospital administrators, laboratory directors, and laboratory supervisors facilitated distribution of the study invitation but were not involved in completing or evaluating individual responses. Participation was voluntary.

3.4 Research Instrument

Data were collected using a researcher-developed structured questionnaire with supplementary open-ended questions. The instrument contained three principal sections.

The first section obtained information on age, years of professional experience, availability of AI-related seminars or workshops in the respondent's institution, and hospital classification.

The second section measured preparedness for AI integration through five statements addressing laboratory readiness, the anticipated usefulness of AI, willingness to learn AI-assisted diagnostic tools, institutional preparedness, and the complementary role of AI in medical technology practice. Responses were rated on a four-point Likert scale from 1 (strongly disagree) to 4 (strongly agree).

The third section measured perceived challenges through 13 statements grouped into financial resources, limited educational opportunities, and inadequate infrastructure. Higher scores represented greater perceived challenges. The positively phrased item concerning the sufficiency of laboratory facilities was reverse-coded before the infrastructure and overall challenge scores were computed.

Mean scores were interpreted as follows: 3.41-4.00, very high; 2.81-3.40, high; 2.21-2.80, moderate; 1.61-2.20, low; and 1.00-1.60, very low.

The questionnaire was reviewed by three medical laboratory professionals for clarity, relevance, and alignment with the study objectives. A separate pilot test involving 31 licensed medical technologists yielded an overall Cronbach's alpha coefficient of .8535, indicating good internal consistency. Supplementary open-ended responses were used only to provide contextual support and were not analyzed as a separate qualitative dataset.

3.5 Data-Gathering Procedure

The study was conducted after institutional and ethics approval had been obtained. Eligible registered medical technologists received study information and an informed-consent form before completing the questionnaire. The instrument was administered onsite in printed form during schedules coordinated with participating hospitals.

Completed questionnaires were collected, checked for completeness, coded, and entered into a password-protected electronic database. No names, employee identification numbers, hospital names, or other directly identifying information were included in the analytical dataset.

3.6 Data Analysis

Frequencies and percentages were used to describe age, years of professional experience, institution-sponsored AI seminars or workshops, and hospital classification. Means and standard deviations were calculated for preparedness indicators, challenge indicators, challenge-domain scores, and overall composite scores.

Kruskal-Wallis H tests were used to examine differences in preparedness and perceived challenge scores according to age group and years of professional experience. Mann-Whitney U tests were used to examine differences according to whether the respondent's institution offered AI-related seminars or workshops. Median scores were used for group comparisons. To control familywise error across the three grouping variables, a Bonferroni-adjusted significance level of .017 was applied. Because some demographic categories contained relatively few respondents, the inferential findings were treated as exploratory and interpreted cautiously.

3.7 Ethical Considerations

The study protocol was reviewed and approved by the Centro Escolar University Institutional Ethics Review Board under protocol code CEU-IERB_SY25-26_1326_MedTech. Written informed consent was obtained from all participants. Participation was voluntary, and respondents could decline to answer any item or withdraw without penalty.

No directly identifying information was included in the analytical dataset. Printed records and encoded files were secured and accessible only to the authorized research team and research adviser. Data management and disposal procedures followed the approved protocol and the Data Privacy Act of 2012.

4. Results and Discussion

4.1 Respondent Characteristics and Institutional AI Exposure

The study included 100 registered medical technologists working in secondary and tertiary hospitals in Metro Manila. Most respondents were between 23 and 30 years old (n = 89, 89.0%), while eight respondents (8.0%) were between 31 and 40 years old and three (3.0%) were between 41 and 50 years old.

The sample was also predominantly composed of early-career professionals. Forty-two respondents (42.0%) had between six months and one year of professional experience, while 41 respondents (41.0%) had between two and five years. Fourteen respondents (14.0%) had six to ten years of experience, and three (3.0%) had at least 11 years of professional practice. Taken together, 83.0% of respondents had five years or less of experience.

Institutional exposure to artificial intelligence was limited. Ninety-one respondents (91.0%) reported that their hospitals did not provide AI-related seminars or workshops, while only nine (9.0%) indicated that such institutional

learning opportunities were available. In terms of hospital classification, 58 respondents (58.0%) were employed in tertiary hospitals and 42 (42.0%) worked in secondary hospitals.

The respondent profile indicates that the findings largely represent the perspectives of younger and relatively early-career medical technologists. At the same time, the limited availability of institution-sponsored AI activities suggests that respondents' views were formed in settings where formal organizational preparation for AI remained uncommon.

4.2 Preparedness for Artificial Intelligence Integration

Table 1 presents respondents' preparedness for the integration of artificial intelligence into soil-transmitted helminth identification.

Table 1. *Preparedness for Artificial Intelligence Integration in Soil-Transmitted Helminth Identification*

Preparedness indicator	Mean	SD	Interpretation
Laboratory readiness for AI integration in STH detection	2.15	0.70	Low
AI as an efficient tool for parasitology within the next five years	2.76	0.74	Moderate
Willingness to learn AI-based diagnostic tools for STH identification	3.05	0.66	High
Institutional preparedness to adopt AI-assisted machines	2.36	0.70	Moderate
AI as a complement to medical technologists in STH diagnostics	2.75	0.63	Moderate
Overall preparedness	2.61	0.51	Moderate

Note. Scale interpretation: 3.41-4.00 = very high; 2.81-3.40 = high; 2.21-2.80 = moderate; 1.61-2.20 = low; and 1.00-1.60 = very low.

The overall preparedness score was moderate (M = 2.61, SD = 0.51). This result indicates that respondents were neither entirely unprepared nor sufficiently equipped to implement AI-assisted soil-transmitted helminth identification in their current laboratory settings.

The highest-rated indicator was willingness to learn AI-based diagnostic tools (M = 3.05, SD = 0.66), interpreted as high. This finding suggests that personal receptiveness to AI was not the principal obstacle to adoption. Respondents appeared open to acquiring the competencies required to use AI-supported diagnostic systems.

By contrast, laboratory readiness received the lowest rating (M = 2.15, SD = 0.70), interpreted as low. Institutional preparedness to adopt AI-assisted equipment was also only moderate (M = 2.36, SD = 0.70). The difference between high willingness to learn and low perceived laboratory readiness indicates a gap between individual openness and organizational capacity.

Respondents moderately agreed that AI could become an efficient tool in parasitology within the next five years (M = 2.76, SD = 0.74) and that AI could complement the work of medical technologists (M = 2.75, SD = 0.63). These results reflect cautious optimism: respondents recognized the possible value of AI but did not perceive their laboratories as currently ready for full implementation.

4.3 Perceived Challenges to Artificial Intelligence Integration

The perceived challenges were organized into financial resources, limited educational opportunities, and inadequate infrastructure. Table 2 presents the composite scores for these domains.

Table 2. *Perceived Challenges to Artificial Intelligence Integration*

Challenge domain	Mean	SD	Interpretation
Financial resources	3.44	0.56	Very high
Limited educational opportunities	3.06	0.49	High
Inadequate infrastructure	3.10	0.41	High
Overall challenges	3.22	0.39	High

Note. Scale interpretation: 3.41-4.00 = very high; 2.81-3.40 = high; 2.21-2.80 = moderate; 1.61-2.20 = low; and 1.00-1.60 = very low. The positively phrased item concerning the sufficiency of laboratory facilities was reverse-coded before computing the infrastructure and overall challenge scores.

The overall challenge score was high (M = 3.22, SD = 0.39), demonstrating that respondents perceived substantial barriers to AI adoption across multiple dimensions.

Financial Resources

Financial resources emerged as the most serious challenge domain (M = 3.44, SD = 0.56), interpreted as very high. The highest individual financial item concerned the cost of AI software and maintenance (M = 3.52, SD = 0.59). Respondents also rated the concentration of laboratory budgets on routine operations rather than AI innovation as a very high challenge (M = 3.50, SD = 0.59).

Other highly rated concerns included lack of funding and resources (M = 3.43, SD = 0.67) and limited access to advanced hardware and laboratory infrastructure (M = 3.42, SD = 0.68). Insufficient financial assistance from institutions or government agencies was likewise rated as a high challenge (M = 3.34, SD = 0.77). These results indicate that AI adoption was perceived as a capital-intensive undertaking involving initial equipment acquisition, software licensing, hardware upgrades, maintenance, and continuing technical support.

Limited Educational Opportunities

Limited educational opportunities received a high challenge rating (M = 3.06, SD = 0.49). The lack of training programs and workshops was rated more strongly (M = 3.27, SD = 0.51) than limited general awareness or understanding of AI among medical technologists (M = 2.85, SD = 0.64).

This pattern suggests that respondents' principal concern was not simply unfamiliarity with AI but the absence of structured professional-development opportunities. The finding is consistent with the profile data showing that only 9.0% of respondents worked in institutions offering AI-related seminars or workshops.

Inadequate Infrastructure

Infrastructure inadequacy was also rated as a high challenge (M = 3.10, SD = 0.41). Respondents identified limited technical support for AI installation and maintenance as a high barrier (M = 3.22, SD = 0.68). Limited access to reliable internet connectivity and digital systems also received a high rating (M = 2.94, SD = 0.68).

Power-related concerns were prominent. Respondents agreed that power outages could compromise AI-generated diagnostic results (M = 3.21, SD = 0.66) and that sudden power loss could interrupt diagnostic processes and produce incomplete outputs (M = 3.29, SD = 0.57). The need to retain proficiency in manual diagnostic procedures during power interruptions received one of the highest infrastructure ratings (M = 3.34, SD = 0.55).

The reverse-coded item concerning the adequacy of laboratory facilities yielded a moderate challenge score (M = 2.57, SD = 0.74). This indicates that respondents did not uniformly perceive their physical facilities as wholly inadequate; however, the broader infrastructure domain remained constrained by technical support, internet reliability, and power continuity.

4.4 Differences According to Respondent Characteristics

Nonparametric analyses were used because the grouping variables were categorical and several groups contained relatively few respondents. Kruskal-Wallis H tests examined differences according to age and years of professional experience, while Mann-Whitney U tests examined differences according to the availability of institution-sponsored AI seminars or workshops. A Bonferroni-adjusted significance level of .017 was applied across the three grouping variables.

Table 3 summarizes the inferential results for preparedness, the three challenge domains, and overall challenges.

Table 3. *Nonparametric Tests of Differences in Preparedness and Perceived Challenges*

Outcome	Age H	p	Experience H	p	Seminar U	p
Preparedness	0.289	.865	3.119	.374	317.000	.263
Financial resources	0.514	.773	0.796	.850	470.000	.458
Educational opportunities	7.009	.030	3.049	.384	328.000	.300

Outcome	Age H	p	Experience H	p	Seminar U	p
Inadequate infrastructure	1.734	.420	1.469	.689	454.500	.589
Overall challenges	1.519	.468	1.380	.710	425.500	.852

Note. Kruskal-Wallis H tests were used for age and years of experience. Mann-Whitney U tests were used for institutional AI seminar/workshop availability. Bonferroni-adjusted alpha = .017. None of the comparisons reached the adjusted significance threshold.

Preparedness did not differ significantly according to age, years of professional experience, or access to institution-sponsored AI seminars or workshops. Overall challenge scores likewise showed no statistically significant differences across these variables.

The domain-level analyses produced the same general pattern. Financial-resource, educational-opportunity, and infrastructure challenge scores did not differ significantly according to years of professional experience or seminar availability. For age, limited educational opportunities produced an unadjusted p value of .030; however, this did not meet the Bonferroni-adjusted significance criterion of .017 and was therefore interpreted as nonsignificant.

The absence of detected differences suggests that preparedness and barriers were broadly shared across respondent groups. These results should nevertheless be interpreted cautiously because the age and experience distributions were highly uneven, with relatively few respondents in the older and more experienced categories.

4.5 Discussion

The findings portray a workforce that is generally receptive to AI but constrained by limited institutional readiness. Respondents demonstrated high willingness to learn AI-assisted diagnostic tools, yet they rated current laboratory readiness as low and overall preparedness as only moderate. This distinction suggests that resistance among medical technologists may not be the primary barrier to adoption. Organizational conditions appear to lag behind professional interest.

This finding is consistent with evidence that healthcare stakeholders often view AI positively when it is framed as a supportive rather than replacement technology. Tursynbek et al. (2024) found that patients recognized the potential of AI to improve diagnostic efficiency but continued to value professional judgment, accountability, and human oversight. Similarly, respondents in the present study moderately agreed that AI could complement medical technologists in soil-transmitted helminth diagnosis.

The cautious optimism expressed by respondents is also consistent with developments in AI-assisted parasitology. Digital microscopy and deep-learning systems have demonstrated the ability to identify, classify, and quantify helminth eggs under laboratory and field conditions (Cure-Bolt et al., 2024; Lee et al., 2022; Lundin et al., 2024; Ward et al., 2022). These technologies may reduce repetitive screening and support diagnostic standardization. However, their benefits depend on local validation, image quality, data availability, and integration into existing laboratory procedures (Kumar et al., 2023; Penpong et al., 2024).

Financial limitations constituted the most prominent barrier. The very high financial challenge score reflects the combined burden of software costs, equipment procurement, maintenance, hardware requirements, and institutional budget priorities. These concerns align with Oduoye et al. (2024), who identified limited funding, infrastructure deficits, and technical-capacity gaps as central barriers to AI implementation in laboratory medicine in low- and middle-income countries. Parija and Poddar (2024) likewise noted that AI applications in parasitic disease control depend on sustained investment in data systems, equipment, and interdisciplinary capacity.

The educational findings further demonstrate that awareness alone is insufficient. Although respondents were willing to learn, 91.0% reported that their institutions did not offer AI-related seminars or workshops. The high rating for lack of training programs indicates that medical technologists require formal opportunities to develop competencies in digital microscopy, AI-assisted interpretation, verification of automated outputs, and recognition of system limitations. This supports the broader observation that Philippine AI readiness depends on workforce development and institutional planning rather than on individual exposure alone (Cucio & Hennig, 2025; Sarmiento et al., 2025).

Infrastructure concerns were not limited to the availability of laboratory equipment. Respondents also emphasized internet reliability, technical support, and power continuity. These findings have direct implications for the design and procurement of AI-supported laboratory systems. Technologies intended for Philippine hospitals

should incorporate offline functionality, local data storage, automatic recovery, and backup-power arrangements where feasible. The concern regarding power interruptions also reinforces the importance of maintaining competence in conventional microscopy. AI should augment rather than displace the manual diagnostic skills required when automated systems are unavailable or when their outputs require verification.

The absence of significant differences according to age, experience, and institutional seminar availability suggests that the principal barriers may be systemic rather than confined to specific demographic groups. Medical technologists across respondent categories encountered broadly similar institutional conditions. However, the highly concentrated age and experience distributions reduce the strength of this conclusion. The nonsignificant results indicate only that differences were not detected within this sample.

The study has several limitations. Purposive sampling and restriction to hospitals in Metro Manila limit generalizability to other regions and facility types. Preparedness was self-reported rather than assessed through objective measures of AI knowledge or performance. The sample was concentrated among younger and early-career respondents, and some comparison groups were small. Hospital classification was described but was not included as a comparative variable in the original analytical plan. Finally, the cross-sectional design captures perceptions at one point in time and cannot determine how preparedness may change following training or technology implementation.

Overall, the study indicates that the implementation of AI-assisted soil-transmitted helminth identification requires a coordinated institutional approach. Workforce willingness provides a favorable starting point, but meaningful adoption depends on financing, structured professional education, reliable infrastructure, technical support, and implementation policies that preserve medical technologists' professional oversight.

5. Conclusions, Recommendations, and Implications

5.1 Conclusions

Registered medical technologists in secondary and tertiary hospitals in Metro Manila demonstrated moderate preparedness for the integration of artificial intelligence into soil-transmitted helminth identification. Their high willingness to learn AI-assisted diagnostic tools indicates a favorable professional disposition toward technological innovation. However, this openness was not matched by comparable laboratory and institutional readiness. Respondents perceived their laboratories as insufficiently prepared for immediate AI implementation, although they generally recognized that AI could become an efficient diagnostic aid and complement the work of medical technologists.

The principal barriers to adoption were institutional rather than attitudinal. Financial-resource constraints constituted the most severe challenge, particularly the cost of AI software and maintenance, limited access to advanced equipment, inadequate funding, and the prioritization of routine laboratory operations over technological innovation. Educational and infrastructural barriers were also substantial. The limited availability of AI-related seminars and workshops, insufficient technical support, unreliable digital connectivity, and concerns regarding power interruptions could impede the safe and sustained operation of AI-assisted diagnostic systems.

The prominence of power-related concerns also confirms that manual microscopy should remain an essential professional competency. AI-supported systems may improve efficiency and standardization, but they cannot be treated as complete replacements for established diagnostic procedures, particularly in settings where electricity, connectivity, maintenance, and technical support are not consistently available.

Preparedness and perceived challenge scores did not differ significantly according to age, years of professional experience, or availability of institution-sponsored AI seminars or workshops under the adjusted significance criterion. Within the limitations of the sample distribution, the findings suggest that concerns regarding AI implementation were broadly experienced across respondent groups rather than confined to a particular age or career stage.

Overall, successful AI integration in soil-transmitted helminth identification requires more than workforce willingness. It depends on coordinated institutional investment, structured competency development, reliable technical infrastructure, locally appropriate system validation, and policies that preserve professional accountability and human oversight.

5.2 Recommendations

Hospital Administrators and Laboratory Managers

Hospitals should conduct formal readiness assessments before procuring AI-assisted parasitology systems. These assessments should examine equipment compatibility, electrical stability, internet connectivity, data-storage capacity, cybersecurity, laboratory workflow, technical staffing, and maintenance requirements. AI adoption should proceed through monitored pilot implementation rather than immediate full-scale deployment.

Dedicated budget provisions should cover hardware acquisition, software licensing, system validation, preventive maintenance, technical support, staff training, and equipment replacement. Procurement decisions should consider total cost of ownership rather than purchase price alone. Systems with offline functionality, local data caching, automatic recovery, secure backup procedures, and compatibility with existing laboratory information systems should be prioritized where appropriate.

Medical Technology Educators and Professional Organizations

Medical technology programs and continuing professional development providers should introduce structured instruction in digital microscopy, AI-assisted image interpretation, data quality, algorithmic limitations, diagnostic verification, ethical use, and data privacy. Training should include applied laboratory exercises rather than being limited to general AI awareness.

Professional organizations may develop competency frameworks defining the knowledge and skills required for medical technologists who operate or validate AI-assisted diagnostic tools. Manual microscopy proficiency should continue to be reinforced because conventional procedures remain necessary when automated systems are unavailable, produce uncertain outputs, or require independent verification.

Government and Health-Policy Institutions

The Department of Health and relevant regulatory bodies should develop guidance for the evaluation, validation, procurement, and use of AI-assisted laboratory technologies. Minimum requirements should address diagnostic accuracy, local validation, data security, human oversight, maintenance, accountability, and reporting of system errors.

Funding and technical-assistance programs may support hospitals that lack resources for digital laboratory modernization. Shared training programs, regional technical-support arrangements, and partnerships among hospitals, universities, professional organizations, and technology developers could reduce implementation costs and prevent fragmented adoption.

Technology Developers and Vendors

Developers should design AI-assisted diagnostic tools suited to the operational realities of Philippine hospitals. Systems should be robust under variable connectivity and power conditions, transparent in their performance limitations, and capable of supporting user verification rather than presenting automated outputs as unquestionable conclusions.

Vendors should provide documented validation evidence, user training, maintenance agreements, software-update policies, data-protection safeguards, and technical support throughout the operational life of the system. Laboratory personnel should be involved in system testing and workflow design before implementation.

Future Researchers

Future studies should include broader geographic representation, more balanced age and experience groups, and larger numbers of institutions. Comparative analyses may examine differences between secondary and tertiary hospitals, public and private facilities, and institutions with varying levels of digital infrastructure.

Subsequent research should assess objective AI competencies rather than relying exclusively on perceived preparedness. Experimental, longitudinal, or implementation studies may evaluate diagnostic accuracy, turnaround time, user performance, cost-effectiveness, workflow effects, and acceptance before and after structured training or pilot deployment.

5.3 Implications of the Study

Implications for Medical Technology Practice

The study indicates that medical technologists are generally receptive to AI-assisted diagnostics but require institutional support to convert willingness into operational competence. AI readiness should therefore be approached as a combined workforce and organizational capability. Professional practice will increasingly require competence in both conventional microscopy and the critical evaluation of automated outputs.

AI integration may alter the role of medical technologists from exclusive manual examination toward a hybrid function involving specimen preparation, digital image acquisition, system supervision, result verification, troubleshooting, quality assurance, and interpretation. This shift reinforces rather than diminishes the importance of professional judgment.

Implications for Healthcare Institutions

Institutional readiness cannot be inferred solely from hospital classification or the availability of advanced equipment. Sustainable implementation requires aligned financing, infrastructure, training, governance, maintenance, and contingency systems. Hospitals that procure AI tools without addressing these conditions risk underutilization, workflow disruption, inaccurate reliance on automated outputs, or premature abandonment of the technology.

The findings support phased implementation beginning with readiness assessment, targeted training, controlled pilot testing, and continuous performance monitoring. Institutional policies should specify when AI outputs require manual confirmation and who retains responsibility for the final laboratory result.

Implications for Patient Care and Public Health

AI-assisted soil-transmitted helminth identification may contribute to more consistent screening, improved documentation, reduced observer variability, and stronger surveillance. These benefits could support earlier detection and more reliable monitoring of parasitic infections. However, patient-care benefits will materialize only when systems are locally validated, properly maintained, and used by adequately trained professionals.

Inaccurate or poorly implemented AI systems could introduce new diagnostic risks. Human verification, quality control, and conventional diagnostic capacity must therefore remain integral to patient safety and public-health surveillance.

Policy Implications

The findings demonstrate the need for national and institutional policies that treat AI adoption as a health-system intervention rather than a simple equipment purchase. Regulation should address technical performance, workforce competence, data governance, infrastructure resilience, ethical accountability, and equitable access.

Policies should also avoid widening technological disparities between well-resourced and resource-constrained hospitals. Funding assistance, shared infrastructure, standardized training, and coordinated implementation may help ensure that AI-supported diagnostic innovation contributes to equitable laboratory improvement rather than increasing institutional inequality.

6. References

Atento, R. G. O., Quinto, L. F., & Espelita, C. A. M. H. (2025). Bridging global health workforce gaps 2050: A multilevel analysis of global demand, Philippine supply fragilities, and competency alignment. *International Journal of Health and Business Analytics, 1*(2), 1–30. https://doi.org/10.65166/kgbpey79

Atento, R. G., Quinto, L., Espelita, C. A. M., & Castaneda, C. (2025). Integrating business and health analytics: A conceptual framework for dual outcomes in healthcare. *International Journal of Health & Business Analytics, 1*(1). https://doi.org/10.65166/04pdc866

Atento, R. G. O., Quinto, L. F., Espelita, C. A. M., & San Juan, F. M. (2025). Narrative health analytics: Integrating empathy, data, and ethics in patient-centered healthcare. *International Journal of Health and Business Analytics, 1*(2), 1–33. https://doi.org/10.65166/yxgx8e59

Bendal, A., Sabasa, S. A., Espelita, C. A. M. H., & Atento, R. G. O. (2026). Artificial intelligence as disruptive technology in accounting: A qualitative study of practitioner perceptions on automation, judgment, and decision support. *Journal of Enterprise Strategy & Management Innovation, 1*(1). https://doi.org/10.65166/0sdayg70

Cucio, M., & Hennig, T. (2025). *Artificial intelligence and the Philippine labor market: Mapping occupational exposure and complementarity* (IMF Working Paper No. 2025/043). International Monetary Fund. https://doi.org/10.5089/9798229001977.001

Cure-Bolt, N., Perez, F., Broadfield, L. A., Levecke, B., Hu, P., Oleynick, J., Beltrán, M., Ward, P., & Stuyver, L. J. (2024). Artificial intelligence-based digital pathology for the detection and quantification of soil-transmitted helminths eggs. *PLOS Neglected Tropical Diseases, 18*(9), e0012492. https://doi.org/10.1371/journal.pntd.0012492

De Niz, M., Silva Pereira, S., Kirchenbuechler, D., Lemgruber, L., & Arvanitis, C. (2026). Artificial intelligence-powered microscopy: Transforming the landscape of parasitology. *Journal of Microscopy, 301*(2), 280-329. https://doi.org/10.1111/jmi.13433

Grau-Pujol, B., Martí-Soler, H., Escola, V., Demontis, M., Jamine, J. C., Gandasegui, J., Muchisse, O., Cambra-Pellejà, M., Cossa, A., Martínez-Valladares, M., Sacoor, C., Van Lieshout, L., Cano, J., Giorgi, E., & Muñoz, J. (2021). Towards soil-transmitted helminths transmission interruption: The impact of diagnostic tools on infection prediction in a low-intensity setting in Southern Mozambique. *PLOS Neglected Tropical Diseases, 15*(10), e0009803. https://doi.org/10.1371/journal.pntd.0009803

He, W., Zhu, H., Geng, J., Hu, X., Li, Y., Shi, H., Wang, Y., Zhu, D., Wang, H., Xie, L., Yang, H., & Li, J. (2024). Recognition of parasitic helminth eggs via a deep learning-based platform. *Frontiers in Microbiology, 15*, 1485001. https://doi.org/10.3389/fmicb.2024.1485001

Kenneth, M. H., Tibakanya, J., & Nakasi, R. (2024). AI methods and algorithms for diagnosis of intestinal parasites: Applications, challenges and future opportunities. *East African Journal of Information Technology, 7*(1), 366-379. https://doi.org/10.37284/eajit.7.1.2282

Kumar, S., Arif, T., Alotaibi, A. S., Malik, M. B., & Manhas, J. (2023). Advances towards automatic detection and classification of parasites microscopic images using deep convolutional neural network: Methods, models and research directions. *Archives of Computational Methods in Engineering, 30*(3), 2013-2039. https://doi.org/10.1007/s11831-022-09858-w

Lee, C. C., Huang, P. J., Yeh, P. H., Li, P. P., Chiu, C. H., Cheng, W. H., & Tang, P. (2022). Helminth egg analysis platform (HEAP): An opened platform for microscopic helminth egg identification and quantification based on the integration of deep learning architectures. *Journal of Microbiology, Immunology and Infection, 55*(3), 395-404. https://doi.org/10.1016/j.jmii.2021.07.014

Lundin, J., Suutala, A., Holmström, O., Henriksson, S., Valkamo, S., Kaingu, H., Kinyua, F., Muinde, M., Lundin, M., Diwan, V., Mårtensson, A., & Linder, N. (2024). Diagnosis of soil-transmitted helminth infections with digital mobile microscopy and artificial intelligence in a resource-limited setting. *PLOS Neglected Tropical Diseases, 18*(4), e0012041. https://doi.org/10.1371/journal.pntd.0012041

Mationg, M. L. S., Tallo, V. L., Williams, G. M., Gordon, C. A., Clements, A. C. A., McManus, D. P., & Gray, D. J. (2021). The control of soil-transmitted helminthiases in the Philippines: The story continues. *Infectious Diseases of Poverty, 10*, Article 85. https://doi.org/10.1186/s40249-021-00870-z

Meulah, B., Bengtson, M., Van Lieshout, L., Hokke, C. H., Kreidenweiss, A., Diehl, J.-C., Adegnika, A. A., & Agbana, T. E. (2023). A review on innovative optical devices for the diagnosis of human soil-transmitted helminthiasis and schistosomiasis: From research and development to commercialization. *Parasitology, 150*(2), 137-149. https://doi.org/10.1017/S0031182022001664

Microsoft Philippines Communications Team. (2024, May 23). *Microsoft and LinkedIn release 2024 Work Trend Index on AI use at work in the Philippines*. Microsoft News Center Philippines. https://news.microsoft.com/en-ph/2024/05/23/microsoft-and-linkedin-release-2024-work-trend-index-on-ai-use-at-work-in-the-philippines/

Miswan, N., Singham, G. V., & Othman, N. (2022). Advantages and limitations of microscopy and molecular detections for diagnosis of soil-transmitted helminths: An overview. *Helminthologia, 59*(4), 321-340. https://doi.org/10.2478/helm-2022-0034

Oduoye, M. O., Fatima, E., Muzammil, M. A., Dave, T., Irfan, H., Fariha, F. N. U., Marbell, A., Ubechu, S. C., Scott, G. Y., & Elebesunu, E. E. (2024). Impacts of the advancement in artificial intelligence on laboratory medicine in low- and middle-income countries: Challenges and recommendations-A literature review. *Health Science Reports, 7*(1), e1794. https://doi.org/10.1002/hsr2.1794

Parija, S. C., & Poddar, A. (2024). Artificial intelligence in parasitic disease control: A paradigm shift in health care. *Tropical Parasitology, 14*(1), 2-7. https://doi.org/10.4103/tp.tp_66_23

Penpong, N., Wanna, Y., Kamjanlard, C., Techasen, A., & Intharah, T. (2024). Attacking the out-of-domain problem of a parasite egg detection in-the-wild. *Heliyon, 10*(4), e26153. https://doi.org/10.1016/j.heliyon.2024.e26153

Rao, L., Tian, Y., & Atento, R. G. O. (2025). Adoption and perceived effectiveness of AI in education: Personalization, outcomes, and equity. *International Journal of Health & Business Analytics, 1*(1). https://doi.org/10.65166/qgq89291

Sarmiento, R. F. R., Overgaard, S. M., Gai, C., Overgaard, J. D., & Ohde, J. W. (2025). Guiding responsible AI in healthcare in the Philippines. *npj Digital Medicine, 8*, Article 338. https://doi.org/10.1038/s41746-025-01755-3

Somono, L., & Generoso, M. J. I. A., II. (2026). IT infrastructure and data privacy practices in manufacturing companies. *Journal of Enterprise Strategy & Management Innovation, 1*(1). https://doi.org/10.65166/dyzqhe81

Tursynbek, A., Zhaksylykova, D., Cruz, J. P., & Balay-Odao, E. M. (2024). Perspectives of patients regarding artificial intelligence and its application in healthcare: A qualitative study. *Journal of Clinical Nursing*. Advance online publication. https://doi.org/10.1111/jocn.17584

Ward, P., Dahlberg, P., Lagatie, O., Larsson, J., Tynong, A., Vlaminck, J., Zumpe, M., Ame, S., Ayana, M., Khieu, V., Mekonnen, Z., Odiere, M., Yohannes, T., Van Hoecke, S., Levecke, B., & Stuyver, L. J. (2022). Affordable artificial intelligence-based digital pathology for neglected tropical diseases: A proof-of-concept for the detection of soil-transmitted helminths and Schistosoma mansoni eggs in Kato-Katz stool thick smears. *PLOS Neglected Tropical Diseases, 16*(6), e0010500. https://doi.org/10.1371/journal.pntd.0010500

World Health Organization. (2023, January 18). *Soil-transmitted helminth infections*. https://www.who.int/news-room/fact-sheets/detail/soil-transmitted-helminth-infections

Xu, W., Zhai, Q., Liu, J., Xu, X., & Hua, J. (2024). A lightweight deep-learning model for parasite egg detection in microscopy images. *Parasites & Vectors, 17*, Article 454. https://doi.org/10.1186/s13071-024-06503-2

Zhu, H., Li, Y., Zhu, D., Wang, Y., Zhang, J., Chen, S., Ma, X., Wang, H., Li, H., & Li, J. (2024). Establishment and application of an artificial intelligence-assisted platform for detection of parasite eggs [Article in Chinese]. *Chinese Journal of Schistosomiasis Control, 36*(6), 643-648. https://doi.org/10.16250/j.32.1374.2024094