

AI Readiness, Perceived Utility, and Professional Integration among Medical Technologists in Cavite: A Socio-Technical Study

Honeylet O. Arancon¹, Maria Teresa F. Mateo¹, Canary Anne B. Cantuba¹, Gallardo C. Dalhag¹, Rendix Rey A. Catindig¹, Dr. Jamilah Baragona²

¹Graduate School Student, MS Clinical Laboratory Science, University of Perpetual Help System Laguna, Philippines

²Co-Researcher, Graduate School, MS Clinical Laboratory Science, University of Perpetual Help System Laguna, Biñan, Laguna, Philippines

Email of Corresponding Author: c25-3191-721@uphsl.edu.ph

Publication history:

Received: September 7, 2026

Revised: October 5, 2026

Accepted: October 7, 2026

Published: October 8, 2026

International Journal of Sustainable and Integrated Studies, Vol. 1, No. 3, pp. 161–166, October 2026.

Abstract

This study assessed the levels of AI readiness, perceived utility, and professional integration of artificial intelligence among medical technologists in selected clinical and hospital laboratories in Cavite and examined the relationships among these variables. Grounded in a socio-technical perspective that integrates the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Socio-Technical Systems Theory, the research employed a descriptive-correlational design. One hundred licensed medical technologists were selected through purposive sampling according to predefined inclusion criteria. AI readiness was measured with the Medical Artificial Intelligence Readiness Scale for Medical Students, perceived utility with the Professional Impact subscale of the Shinnars Artificial Intelligence Perception questionnaire, and professional integration with items adapted from the Unified Theory of Acceptance and Use of Technology. Data were analyzed using descriptive statistics and Spearman's rank-order correlation. Respondents demonstrated high levels of AI readiness (mean = 3.60) and perceived utility (mean = 3.64), indicating adequate knowledge, technical skills, and positive perceptions toward AI use in laboratory practice. Professional integration was also rated high (mean = 3.61), although AI remained only moderately embedded in routine workflows and many respondents were neutral regarding the actual extent of use. Correlation analyses revealed very weak, non-significant relationships among the three constructs, indicating that individual readiness and favorable perceptions did not translate into greater professional integration. The findings suggest that organizational and contextual factors—such as institutional support, infrastructure, and policy implementation—play a more decisive role in AI adoption than individual-level attributes alone. The study recommends structured, hands-on AI training programs tailored to laboratory practice, clear institutional policies and protocols for incorporating AI outputs into diagnostic workflows, and future research employing probability sampling, multi-regional samples, and longitudinal designs. The research contributes to Sustainable Development Goal 3 by supporting improved diagnostic capacity and laboratory-enabled clinical decision-making, and to Sustainable Development Goal 9 by examining the conditions required for sustainable adoption of innovative health technologies. It advances public-health and

institutional sustainability by clarifying the socio-technical determinants that enable resilient, digitally enabled laboratory services in resource-constrained settings.

Keywords: Artificial Intelligence; AI Readiness; Clinical Laboratory; Medical Technologists; Perceived Utility; Philippines; Professional Integration; Socio-Technical

1. Introduction

The global healthcare landscape is rapidly transforming through the widespread adoption of artificial intelligence (AI) in clinical and laboratory settings. AI technologies, including machine learning, deep learning, and natural language processing, are increasingly used in disease diagnosis, patient monitoring, laboratory automation, and clinical decision support (Secinaro et al., 2021). These advancements have enhanced diagnostic accuracy, reduced turnaround times, and improved patient outcomes, particularly in imaging analysis, pathology interpretation, and genomic profiling (Rajpurkar et al., 2022). In clinical laboratories, AI integration has significant implications because laboratory results inform approximately 70% of medical decisions (Alowais et al., 2023). AI-driven systems such as automated sample processing, predictive diagnostic algorithms, and intelligent quality control tools are reshaping laboratory workflows and the professional roles of medical technologists. As these technologies become embedded in routine practice, important questions arise regarding technologists' readiness, perceived usefulness of AI, and extent of AI integration in daily laboratory work.

Artificial intelligence has rapidly evolved into a central component of modern healthcare. Advances in machine learning, deep learning, and the growing availability of health data have enabled AI systems to identify patterns in complex datasets with performance approaching that of human experts in some fields (Topol, 2024). Secinaro et al. (2021) identified major AI applications including clinical decision support, diagnostic imaging, natural language processing, drug discovery, and administrative automation. Rajpurkar et al. (2022) highlighted AI's strongest clinical applications in radiology, pathology, ophthalmology, and cardiology. The World Health Organization (2021) established ethical guidelines emphasizing transparency, inclusiveness, accountability, fairness, security, and adaptability. Laboratory medicine is among the fields most affected by AI due to its reliance on structured quantitative data suitable for machine learning (Alowais et al., 2023). Applications include automated cell differentials, AI-assisted mass spectrometry interpretation, and deep learning for whole-slide imaging (Secinaro et al., 2021). Despite benefits, challenges persist, including alert fatigue, limited generalizability, and over-reliance on automated outputs (Bates et al., 2021), underscoring the need for technical knowledge, critical thinking, and confidence among professionals.

The Technology Acceptance Model (Davis, 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) identify perceived usefulness, ease of use, performance expectancy, social influence, and facilitating conditions as key determinants of technology acceptance. Socio-Technical Systems Theory emphasizes that successful implementation depends on both technical systems and organizational and social environments (Salwei & Carayon, 2022). Studies on AI readiness show limited preparedness among healthcare professionals. Russell et al. (2023) emphasized the need for AI literacy, practical experience, and critical appraisal skills. Weidener and Fischer (2024) found that workers with prior AI-related training reported greater confidence, although many lacked such preparation. Lambert et al. (2023) noted that attitudes were influenced by professional identity, with some viewing AI as a threat and others as an enhancement. Huisman et al. (2021) observed greater AI exposure and confidence among younger professionals and those in academic institutions. Perceived utility is strongly associated with adoption when AI addresses clear clinical needs and produces understandable outputs (Lambert et al., 2023; Weidener & Fischer, 2024). Institutional support, staff orientation, and feedback mechanisms further influence perceived utility and use (Huisman et al., 2021; Alowais et al., 2023). Professional integration remains constrained by limited understanding of how AI systems function (Russell et al., 2023). Despite the growing use of AI in healthcare, limited empirical research explores the experiences of frontline laboratory personnel, particularly in developing countries. In the Philippines, medical technologists work within resource-constrained healthcare systems while facing increasing patient demands. Although the Department of Science and Technology (DOST, 2021) has introduced a national AI roadmap for healthcare, its translation into laboratory-level practice remains unclear. Cavite, with its rapidly expanding healthcare infrastructure combining government and private hospitals as well as independent diagnostic laboratories, provides an important setting for examining AI readiness and integration among frontline laboratory professionals. Since most studies on AI adoption have been conducted in high-income countries (WHO, 2021), this study contributes evidence within the context of developing-country allied health practice. This study is anchored on three interconnected theoretical foundations: the Technology Acceptance Model (TAM) by Davis (1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), and Socio-Technical Systems (STS) Theory as elaborated by Salwei and Carayon (2022).

TAM posits two primary determinants of technology use: perceived usefulness (the extent to which an individual believes a technology enhances job performance) and perceived ease of use (the degree to which the technology is expected to be free of cognitive effort). These perceptions shape attitudes, which influence behavioral intention and actual usage (Davis, 1989). UTAUT identifies four key determinants of usage intention: performance

expectancy, effort expectancy, social influence, and facilitating conditions, providing a basis for conceptualizing perceived utility as encompassing both functional value and contextual factors in clinical laboratory practice.

STS Theory asserts that organizations are integrated systems of interdependent social and technical components, with performance contingent on the joint optimization of both (Salwei & Carayon, 2022). Applied to the clinical laboratory, successful AI integration depends critically on human factors—including knowledge, attitudes, and professional values of medical technologists—as well as organizational structures and conditions.

TAM and UTAUT operate at the individual level, elucidating how beliefs about AI influence intentions and integration. STS Theory functions at the organizational level, situating individual perceptions within broader institutional, social, and structural conditions. AI adoption in laboratory medicine is therefore an inherently socio-technical phenomenon. Within the conceptual framework, AI readiness and perceived utility are independent variables, while professional integration of AI is the dependent variable. Higher levels of readiness and perceived utility are hypothesized to be positively associated with greater professional integration. Demographic variables (age, sex, years of professional experience, type of laboratory setting, and area of specialization) serve as descriptive factors.

Previous studies suggest that healthcare workers' attitudes toward AI are influenced by professional identity, institutional culture, and familiarity with digital technologies (Lambert et al., 2023; Weidener & Fischer, 2024). Effective AI adoption requires continuous professional development and digital literacy (Russell et al., 2023). However, limited empirical research addresses frontline laboratory personnel in developing-country settings, and the translation of the Philippine national AI roadmap (DOST, 2021) into laboratory practice remains unclear.

Grounded in a socio-technical perspective, this study assessed the relationship between AI readiness, perceived utility, and professional integration of AI among medical technologists in selected clinical and hospital laboratories in Cavite. It aims to contribute baseline evidence on AI adoption in Philippine laboratory medicine and support the development of context-appropriate strategies for AI integration among allied health professionals. The study addressed levels of AI readiness (knowledge of AI tools, technical competencies, and access to training and institutional support), perceived utility (usefulness in laboratory workflows and compatibility with existing practices), and professional integration (frequency of use and incorporation into clinical decision-making), as well as the relationships between readiness and integration, and between perceived utility and integration.

The study aligns primarily with SDG 3 (Good Health and Well-Being) by examining factors that influence the effective integration of AI tools capable of enhancing diagnostic accuracy, efficiency, and laboratory support for clinical decision-making. It also aligns with SDG 9 (Industry, Innovation and Infrastructure) through its focus on the adoption of innovative AI technologies within clinical laboratory systems and the organizational conditions required for their sustainable deployment. Secondary alignment exists with SDG 4 (Quality Education) insofar as findings underscore the need for structured AI literacy and training programs for medical technologists, and with SDG 17 (Partnerships for the Goals) by generating evidence that can inform multi-stakeholder efforts involving educational institutions, health facilities, and national agencies such as DOST, CHED, and DOH.

The research contributes to public health sustainability by identifying barriers and enablers that affect the reliable integration of AI into laboratory workflows that underpin a large proportion of medical decisions. It advances technological and innovation sustainability by clarifying how individual readiness and perceptions interact with institutional infrastructure and policy environments in a resource-constrained setting. Institutional sustainability is addressed through evidence supporting the development of clear protocols, training structures, and accreditation-aligned guidelines for AI adoption. Collectively, these contributions support more resilient, digitally enabled laboratory services that can sustain improved diagnostic capacity and equitable health system performance over time.

2. Material and methods

2.1 Research Design

A descriptive-correlational research design grounded in a socio-technical systems perspective was utilized. The descriptive component assessed the levels of AI readiness, perceived utility, and professional integration among respondents, while the correlational component examined the relationships among these variables. This non-experimental, cross-sectional design is appropriate for examining naturally occurring variables without manipulation (Polit & Beck, 2021).

2.2 Locale of the Study

The study was conducted in selected clinical and hospital laboratories in Cavite, Philippines. The province hosts a combination of government and private hospitals, as well as independent diagnostic laboratories, providing varied organizational settings and levels of AI exposure.

2.3 Respondents of the Study

The respondents consisted of 100 licensed medical technologists employed in selected laboratories in Cavite. Participants were required to possess a valid PRC Medical Technologist license, be currently employed in a clinical or hospital laboratory in Cavite, have at least six months of work experience, and voluntarily agree to

participate. Individuals on extended leave, retired personnel, those working outside laboratory settings, and those employed in research, forensic, industrial, or environmental laboratories were excluded from the study.

2.4 Sample and Sampling Procedure

Purposive sampling was used based on the following inclusion criteria: possession of a valid PRC Medical Technologist license, current employment in a clinical or hospital laboratory in Cavite, at least six months of work experience, and voluntary consent to participate. Those on extended leave, retired, employed outside laboratory settings, or working in research, forensic, industrial, or environmental laboratories were excluded. The sample size was considered adequate for descriptive-correlational studies (Cohen, 1992; Polit & Beck, 2021).

2.5 Research Instrument

Data were collected using a structured self-administered questionnaire consisting of four parts. Part I gathered demographic and professional information. Part II measured AI readiness using the 22-item Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) developed by Karaca et al. (2021), covering cognition, ability, vision, and ethics. Permission to use the instrument was secured from the original authors. Part III assessed perceived utility using the Professional Impact of AI subscale of the Shinnars Artificial Intelligence Perception (SHAIP) questionnaire (Shinnars et al., 2022). Part IV measured professional integration using eight items adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003). Instrument validity was based on the use of previously validated scales from published studies. A pilot test involving 10 licensed medical technologists outside the study sample was conducted to assess reliability. Cronbach's alpha values ranged from 0.82 to 0.95, indicating good to excellent internal consistency. The MAIRS-MS obtained an overall $\alpha = 0.95$, the SHAIP perceived utility scale $\alpha = 0.95$, and the UTAUT-adapted professional integration scale $\alpha = 0.92$. No revisions were necessary.

2.6 Data Gathering Procedure

The questionnaire was distributed through Google Forms via laboratory heads of participating institutions. An informed consent statement preceded the survey, and responses were securely stored and accessible only to the principal researcher. Data collection continued until 100 complete responses were obtained.

2.7 Data Analysis Techniques

Statistical analysis included frequency and percentage distributions for demographic data, mean and standard deviation for AI readiness, perceived utility, and professional integration, and Spearman's rank-order correlation to determine relationships among variables at a 0.05 significance level. IBM SPSS Statistics Version 26 was used for data analysis. To minimize common method bias, anonymity was maintained and respondents were encouraged to answer honestly. However, the use of purposive sampling and self-reported data may limit the generalizability of findings. Mean scores were interpreted using established ranges corresponding to strongly agree (very high) through strongly disagree (very low), and correlation magnitudes followed standard benchmarks for negligible to very strong relationships (Cohen, 1992).

2.8 Ethical Considerations

The study adhered to the ethical guidelines established by the Philippine Health Research Ethics Board (PHREB). Participation was voluntary and anonymous, and no personally identifiable information was collected from respondents. Informed consent was obtained prior to participation, and all responses were handled confidentially and stored securely.

3. Results and Discussion

3.1 Profile of Respondents

Respondents ranged in age from 25 to 63 years, with a mean age of approximately 38 years and a standard deviation of 13.47, indicating a relatively wide age spread. The sample was predominantly female (61 percent), with males comprising 39 percent. In terms of professional experience, 40 percent had more than 10 years, 28 percent had 4–6 years, 19 percent had 1–3 years, and 13 percent had 7–10 years, reflecting a mix of early-career and highly experienced professionals. Laboratory affiliation was balanced, with 38 percent working in private hospital-based laboratories, 33 percent in government hospital-based laboratories, and 29 percent in independent or freestanding clinical laboratories.

These demographic characteristics provide important context for interpreting AI-related constructs, as prior research has linked age, institutional setting, and professional experience to variations in AI exposure and confidence (Huisman et al., 2021).

3.2 Levels of AI Readiness

Overall, AI readiness was high ($M = 3.60$, $SD = 0.26$). Subscale means were similarly high: cognition ($M = 3.60$, $SD = 0.36$), ability ($M = 3.58$, $SD = 0.43$), vision ($M = 3.62$, $SD = 0.61$), and ethics ($M = 3.66$, $SD = 0.65$). For knowledge of AI tools, 71 percent of respondents agreed or strongly agreed that they were knowledgeable, while

29 percent remained neutral. For technical skills relevant to AI systems, 62 percent agreed or strongly agreed, with 38 percent neutral. Access to AI-related training and institutional support was rated positively by 69 percent (agree or strongly agree), with 31 percent neutral. No respondents selected disagree or strongly disagree on these items. The high overall readiness scores indicate adequate knowledge, technical skills, and positive orientations toward AI among the medical technologists surveyed. However, the substantial proportions of neutral responses on knowledge, skills, and training access suggest that familiarity remains general rather than deeply applied for a sizable subset of the workforce. This pattern is consistent with observations that many healthcare professionals still lack structured, hands-on AI preparation despite growing conceptual awareness (Russell et al., 2023; Weidener & Fischer, 2024).

3.3 Levels of Perceived Utility

Perceived utility was high overall ($M = 3.64$, $SD = 0.34$). Regarding usefulness of AI in diagnostic and laboratory workflows, 60 percent agreed or strongly agreed, 39 percent were neutral, and only 1 percent disagreed. Perceptions of compatibility and ease of use within current professional practice were favorable for 71 percent (agree or strongly agree), with 26 percent neutral and 3 percent disagreeing. These results reflect generally positive views of AI's potential to enhance efficiency and accuracy, together with openness to integration provided tools are user-friendly and aligned with existing protocols. The sizable neutral segments, however, point to limited direct exposure or still-emerging tangible benefits in daily practice, a finding that aligns with reports that perceived utility strengthens primarily when professionals encounter clear clinical applications and understandable outputs (Lambert et al., 2023; Weidener & Fischer, 2024).

3.4 Levels of Professional Integration

Professional integration was rated high overall ($M = 3.61$, $SD = 0.39$). Frequency of AI use across laboratory tasks showed 60 percent agreeing or strongly agreeing, 38 percent neutral, and 2 percent disagreeing (subscale $M = 3.51$, $SD = 0.55$). Incorporation of AI outputs into clinical decision-making was higher, with 83 percent agreeing or strongly agreeing, 15 percent neutral, and 2 percent disagreeing (subscale $M = 3.72$, $SD = 0.51$). While overall ratings were high, the notable neutral responses on frequency of use indicate uneven embedding of AI into routine workflows across roles, departments, or institutions. Where AI tools are available, their outputs appear to be actively considered in clinical judgments, underscoring AI's emerging decision-support role. This pattern of moderate actual use despite high receptivity is consistent with evidence that structural and access barriers often constrain translation of positive attitudes into routine practice (Russell et al., 2023).

3.5 Relationships Among AI Readiness, Perceived Utility, and Professional Integration

Shapiro–Wilk testing indicated that AI readiness ($p = 0.806$) and perceived utility ($p = 0.157$) did not significantly deviate from normality, whereas professional integration ($p = 0.037$) did. Spearman's rank-order correlations revealed very weak, non-significant associations: AI readiness with perceived utility ($\rho = -0.075$, $p = 0.458$), AI readiness with professional integration ($\rho = -0.026$, $p = 0.797$), and perceived utility with professional integration ($\rho = 0.023$, $p = 0.823$). All p -values exceeded 0.05; therefore, both null hypotheses were retained. The absence of statistically significant relationships indicates that higher individual readiness and more favorable perceptions of utility did not translate into greater professional integration in this sample. This finding departs from patterns observed in higher-resource settings, where formal training has been linked to increased confidence and engagement (Weidener & Fischer, 2024) and where direct experience with specific tools strengthens utility perceptions (Lambert et al., 2023). The results instead support the view that institutional affiliation, infrastructure, and organizational support are stronger predictors of actual integration than individual preparedness alone (Huisman et al., 2021; Russell et al., 2023). In the Philippine laboratory context, limited availability of structured AI training programs and uneven distribution of AI-enabled equipment likely attenuate the pathway from readiness and positive perceptions to routine use, reinforcing the centrality of socio-technical and systemic determinants.

4. Conclusion & Recommendations

This study examined the relationships between AI readiness, perceived utility, and professional integration among medical technologists in Cavite using a socio-technical framework. Respondents demonstrated favorable levels of readiness and perceived utility, yet these individual-level factors were not significantly associated with the extent of AI integration in professional practice. The lack of statistically significant relationships indicates that positive attitudes and preparedness alone are insufficient to ensure meaningful adoption of AI technologies in clinical laboratory settings. Instead, broader socio-technical determinants—including organizational infrastructure, institutional support, policy frameworks, and access to technological resources—play a critical role. These results underscore the importance of a systems-oriented approach that strengthens both human and structural dimensions to support sustainable AI integration in laboratory medicine.

Institutions should invest in structured AI training programs tailored to the clinical laboratory context that move beyond passive awareness to hands-on skill development and critical appraisal of AI outputs. Hospital

administrators and laboratory managers should establish clear institutional policies for AI tool adoption, including defined protocols for integrating AI outputs into diagnostic workflows. For future research, probability sampling methods and larger multi-regional samples are recommended to improve generalizability, while longitudinal studies tracking changes in AI readiness and integration over time would further illuminate the dynamic pathways through which individual and organizational factors interact.

5. Compliance with ethical standards

This study was conducted in accordance with the ethical guidelines of the Philippine Health Research Ethics Board (PHREB). Participation was voluntary. An informed consent statement was presented prior to the survey, and respondents could withdraw at any time without consequence. No personally identifiable information was collected, and all responses were kept anonymous and confidential. Data were securely stored and accessible only to the principal researcher.

REFERENCES

- Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., Alduhailib, S., Aloqilah, M., Alswed, A., Alzakil, H., & Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, 23(1), 689. <https://doi.org/10.1186/s12909-023-04698-z>
- Bates, D. W., Levine, D., Syrowatka, A., Kuznetsova, M., Craig, K. J. T., Rui, A., Purcell, G., Jackson, G. P., & Rhee, K. (2021). The potential of artificial intelligence to improve patient safety: A scoping review. *npj Digital Medicine*, 4(1), Article 54. <https://doi.org/10.1038/s41746-021-00423-6>
- Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Department of Science and Technology – Philippines. (2021). Artificial intelligence roadmap of the Philippines. DOST. <https://icts.dost.gov.ph/ai-roadmap>
- Huisman, M., Ranschaert, E., Parker, W., Mastrodicasa, D., Koci, M., de Rooij, M., & van Ooijen, P. M. A. (2021). An international survey on AI in radiology in 191 radiologists and radiology residents part 1: Demographics, current usage, and attitudes toward AI. *European Radiology*, 31(9), 7058–7066. <https://doi.org/10.1007/s00330-021-07781-5>
- Karaca, O., Çalışkan, S. A., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS) – development, validity and reliability study. *BMC Medical Education*, 21(1), 112. <https://doi.org/10.1186/s12909-021-02546-6>
- Lambert, S. I., Madi, M., Sopka, S., Lenes, A., Stange, H., Buszello, C.-P., & Stephan, A. (2023). An integrative review on the acceptance of artificial intelligence among healthcare professionals in hospitals. *npj Digital Medicine*, 6(1), Article 111. <https://doi.org/10.1038/s41746-023-00852-5>
- Polit, D. F., & Beck, C. T. (2021). *Nursing research: Generating and assessing evidence for nursing practice* (11th ed.). Wolters Kluwer.
- Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, 28(1), 31–38. <https://doi.org/10.1038/s41591-021-01614-0>
- Russell, R. G., Lovett Novak, L., Patel, M., Garvey, K. V., Craig, K. J. T., Jackson, G. P., Moore, D., & Miller, B. M. (2023). Competencies for the use of artificial intelligence-based tools by health care professionals. *Academic Medicine*, 98(3), 348–356. <https://doi.org/10.1097/ACM.0000000000004963>
- Salwei, M. E., & Carayon, P. (2022). A sociotechnical systems framework for the application of artificial intelligence in health care delivery. *Journal of Cognitive Engineering and Decision Making*, 16(4), 194–206. <https://doi.org/10.1177/15553434221097357>
- Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V., & Biancone, P. (2021). The role of artificial intelligence in healthcare: A structured literature review. *BMC Medical Informatics and Decision Making*, 21(1), 125. <https://doi.org/10.1186/s12911-021-01488-9>
- Shinners, L., Grace, S., Smith, S., Stephens, A., & Aggar, C. (2022). Exploring healthcare professionals' perceptions of artificial intelligence: Piloting the Shinners Artificial Intelligence Perception tool. *Digital Health*, 8. <https://doi.org/10.1177/20552076221100576>
- Topol, E. J. (2024). *Ground truths: Navigating medicine and science in the age of misinformation*. Columbia University Press.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Weidener, L., & Fischer, M. (2024). Medical students' AI literacy and attitudes towards AI: A cross-sectional two-center study. *BMC Medical Education*, 24, 413. <https://doi.org/10.1186/s12909-024-05400-7>
- World Health Organization. (2021). *Ethics and governance of artificial intelligence for health*. WHO. <https://www.who.int/publications/i/item/9789240029200>