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Perceptions and Readiness Toward Artificial Intelligence Integration Among Medical Laboratory Technicians: A Multi-Center Cross-Sectional Study in Western Libya

Sobheia Miloud ALhoush [1*], Amina Mohammed Abozied[2] and Heba Soliman Alhammali[3]

[1,2,3,] Department of Medical Laboratory Technology, Higher Institute of Medical Sciences, Al-Zahraa, Libya.

www.sobheiamiloud164512@gmail.com
www.myotama2005@gmail.com
www.hs8909720@gmail.com

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Abstract:

Background: Integrating artificial intelligence (AI) into clinical laboratory medicine holds immense potential for optimizing diagnostic workflows. However, technological adoption depends heavily on workforce readiness, baseline digital literacy, and professional trust.

Objective: This study evaluated baseline awareness, diagnostic trust, and professional attitudes among medical laboratory personnel regarding AI integration in clinical result interpretation in Northwestern Libya.

Methods: A quantitative, multi-center cross-sectional study was conducted across eight public and private diagnostic facilities ($N = 100$). Data were collected using a validated structured survey assessing socio-demographic profiles, AI knowledge, diagnostic confidence, and technological trust. Statistical analyses were executed using SPSS (Version 26.0), employing descriptive metrics, Chi-square tests of independence, and Pearson correlation analyses.

Results: Public hospitals employed 50.0% of respondents, with Bachelor's (48.0%) and Higher Diploma (40.0%) degrees dominating academic qualifications. Although 56.0% reported moderate AI knowledge, 37.0% acknowledged significant knowledge deficits. Pronounced skepticism was evident, with 49.0% distrusting AI accuracy and 50.0% doubting its independent error-detection capacity. Academic attainment showed no statistically significant association with manual interpretation confidence ($\chi^2 = 5.664, p = 0.932$). Conversely, a statistically significant positive correlation emerged between cumulative years of laboratory experience and confidence in AI handling complex diagnostic data ($r = 0.225, p = 0.025$).

Conclusion: Medical laboratory professionals exhibit moderate awareness coupled with cautious skepticism toward AI. Experiential tenure enhances trust in complex computational analysis. Successful clinical AI integration requires structured informatics training and strict preservation of human-in-the-loop oversight.

Keywords: Artificial Intelligence, Clinical Diagnostics, Laboratory Medicine, Technological Readiness, Diagnostic Trust, Digital Health.

1- Introduction

The continuous transformation of contemporary healthcare systems relies heavily on enhancing diagnostic precision, operational efficiency, and patient outcomes [1, 2]. Over recent decades, clinical medicine has shifted from rudimentary heuristics toward a sophisticated, data-driven framework where laboratory science occupies a central role [3, 4]. Modern decision-making—ranging from early disease detection to therapeutic monitoring—depends fundamentally on quantitative laboratory datasets [5, 6]. However, expanding global populations and rapid biomedical advancements have

generated unprecedented analytical workloads, overburdening diagnostic infrastructure with complex biological data [6, 7].

Historically, healthcare institutions countered these pressures through mechanical automation and high-throughput analyzers [7, 8]. Today, the principal challenge extends beyond sample processing speed to the cognitive burden of interpreting high-dimensional diagnostic data [8, 9]. This bottleneck has accelerated the adoption of Artificial Intelligence (AI) and machine learning within clinical laboratories [9, 10]. Within this ecosystem, AI functions strictly as a clinical decision support tool rather than a substitute for human expertise [10, 11]. Its primary utility lies in flagging critical deviations, detecting subtle pathological patterns, and streamlining post-analytical interpretation [11, 12]. By alleviating cognitive fatigue, AI assists professionals while preserving ultimate verification authority within human hands [12, 13].

Despite these technological advantages, successful AI integration depends critically on workforce readiness and human factors [13, 14]. Transitioning to AI-augmented environments requires technical personnel to possess adequate digital literacy, psychological readiness, and trust in algorithmic outputs [14, 15]. Without proper technical understanding, staff may experience automation anxiety or exhibit resistance toward system adoption [1, 15]. Consequently, evaluating baseline technological awareness, organizational trust, and professional attitudes among laboratory personnel is an essential prerequisite for seamless deployment [2, 14].

In developing healthcare settings, particularly within the North African and Libyan health sectors, deploying AI in routine practice remains an emerging concept amidst ongoing infrastructural transitions [3, 15]. Existing literature reveals a critical empirical gap regarding how regional laboratory personnel perceive these digital shifts [4, 14]. Limited exposure to health informatics and misconceptions surrounding system boundaries can hinder technological acceptance in local facilities [5, 15]. Establishing an empirical baseline of workforce readiness is therefore paramount to inform national digital health strategies [6, 14]. To address this gap, this study aims to evaluate the awareness, digital literacy, and professional attitudes of medical laboratory technicians regarding AI integration into diagnostic workflows, while assessing their degree of trust in AI outputs and identifying key technical, educational, and organizational barriers to its local operational adoption .

2-Methodology

Study Design & Settings

This observational cross-sectional study evaluated the technological readiness and professional attitudes of laboratory personnel regarding artificial intelligence (AI) integration. Fieldwork spanned eight diverse clinical facilities across northwestern Libya—incorporating public hospitals, specialized reference laboratories, private diagnostic clinics, and primary healthcare centers—to ensure a representative cross-section of varying workloads and infrastructural capacities.

Population & Sampling

The target population comprised actively practicing medical laboratory specialists holding verification authority over diagnostic results. Due to shift rotations and clinical constraints, a convenience sampling strategy was employed, securing a final analytical cohort of $N = 100$ qualified professionals. Inclusion required active clinical employment and direct involvement in testing phases, while administrative staff, phlebotomists, and student trainees were excluded.

Instrument & Psychometric Validation

Data were collected using a structured, self-administered questionnaire divided into four thematic domains: socio-demographic characteristics, diagnostic self-efficacy, baseline AI awareness, and attitudinal trust metrics. Face and content validity were established via an expert panel of clinical pathologists. Internal consistency was empirically confirmed using Cronbach's alpha ($\alpha \geq 0.70$).

Data Processing & Ethics

Surveys were distributed during non-operational intervals following institutional administrative approvals. Complete data anonymity was preserved by omitting direct personal identifiers, with informed consent implied upon voluntary submission. Raw datasets were audited and analyzed using IBM SPSS (Version 26.0). Categorical variables were summarized using frequencies and percentages, while non-parametric tests (including Chi-Square and Linear-by-Linear associations) evaluated independence across variables, maintaining a significance threshold of $p < 0.05$.

3-Results

Baseline Characteristics of the Study Cohort

This section details the descriptive statistics mapping the socio-demographic, academic, and professional baseline profiles of the participating medical laboratory professionals (N = 100).

Institutional Sector Distribution

The primary employment sector of the surveyed laboratory workforce was evaluated across public and private diagnostic environments.

Table 1: ***Distribution of Institutional Work Settings Among Laboratory Technicians (N = 100)***

Place of Work	Frequency (n)	Percentage (%)
Government Hospital	50	50.0%
Private Laboratory	34	34.0%
Private Hospital	15	15.0%
Other Facilities	1	1.0%
Total	100	100.0%

The empirical data demonstrate that half of the surveyed cohort (50.0%, n = 50) operates within public government hospitals, highlighting the central diagnostic role played by state healthcare infrastructure. Independent private laboratories represent the second-largest operational sector (34.0%, n = 34), reflecting a strong private sector involvement in diagnostic services. Private hospitals (15.0%, n = 15) and other community clinics (1.0%, n = 1) represent smaller workforce segments, indicating that clinical laboratory practice is predominantly centered in major public facilities and specialized reference laboratories.

Academic Qualification Levels

The educational attainment profiles of the respondent population were mapped to evaluate baseline professional qualifications.

Table 2: ***Academic Qualifications of the Participating Workforce (N = 100)***

Educational Qualification	Frequency (n)	Percentage (%)
Bachelor's Degree	48	48.0%
Higher Diploma or Equivalent	40	40.0%
Master's Degree	8	8.0%
Doctorate (Ph.D.)	2	2.0%
Other Qualifications	2	2.0%
Total	100	100.0%

The academic distribution highlights an undergraduate-dominated workforce, with Bachelor's degree holders comprising 48.0% (n = 48) and Higher Diploma holders representing 40.0% (n = 40) of the total sample. Post-graduate qualifications remain comparatively limited, with Master's degrees accounting for 8.0% (n = 8) and Doctorates representing 2.0% (n = 2). This educational breakdown indicates a strong technical foundation; however, the low proportion of advanced degree holders suggests that specialized digital health and health informatics training may be required to facilitate the integration of complex AI diagnostic tools.

Practical Laboratory Experience Tenure

Cumulative years of professional laboratory practice were categorized across five distinct experience tiers.

Table 3: ***Professional Experience Tenure Among Laboratory Technicians (N = 100)***

Years of Experience	Frequency (n)	Percentage (%)
Less than 1 year	13	13.0%

1–3 years	28	28.0%
4–6 years	21	21.0%
7–10 years	14	14.0%
More than 10 years	24	24.0%
Total	100	100.0%

The experience profile reflects a well-balanced distribution across early-career, mid-level, and senior laboratory professionals. Early-career technicians (1–3 years) formed the largest group (28.0%, n = 28), followed closely by highly experienced specialists with over ten years of active clinical service (24.0%, n = 24). Mid-level personnel with 4–6 years and 7–10 years of tenure represented 21.0% (n = 21) and 14.0% (n = 14) respectively. This heterogeneous tenure profile allows for meaningful evaluations of how accumulated clinical exposure influences technological trust and diagnostic self-efficacy.

Diagnostic Interpretation Self-Efficacy

Self-assessed confidence in interpreting routine and complex clinical laboratory results was recorded across four agreement levels.

Table 4: ***Self-Reported Confidence in Manual Result Interpretation (N = 100)***

Confidence Level	Frequency (n)	Percentage (%)
Always confident	30	30.0%
Sometimes confident	66	66.0%
Not confident	2	2.0%
Uncertain	2	2.0%
Total	100	100.0%

Two-thirds of the respondents (66.0%, n = 66) reported feeling only "sometimes confident" in manually interpreting laboratory test outputs, whereas less than a third (30.0%, n = 30) exhibited unwavering diagnostic confidence ("always confident"). A minor fraction expressed explicit lack of confidence (2.0%, n = 2) or general uncertainty (2.0%, n = 2). These findings reveal a widespread, conditional self-efficacy that may stem from analytical complexity, high daily workloads, or variable case difficulty, creating a favorable landscape for assistive decision-support tools.

Perception of Clinical Result Relevance

Respondents evaluated the fundamental importance of thorough result comprehension in clinical practice.

Table 5: ***Perceived Importance of Result Comprehension in Patient Care (N = 100)***

Importance Level	Frequency (n)	Percentage (%)
Very important	68	68.0%
Somewhat important	24	24.0%
Neutral	7	7.0%
Not important at all	1	1.0%
Total	100	100.0%

An overwhelming majority of technicians (68.0%, n = 68) affirmed that deep comprehension of laboratory findings is "very important" to diagnostic integrity and patient management, with an additional 24.0% (n = 24) rating it as "somewhat important." Only a minimal fraction expressed neutrality (7.0%) or complete disregard (1.0%). This high consensus reflects a strong professional awareness of the direct linkage between laboratory precision and downstream medical decision-making.

Baseline Awareness of Healthcare AI

Self-reported digital literacy and familiarity with artificial intelligence applications in medicine were surveyed.

Table 6: *Self-Perceived Knowledge Level Regarding Healthcare Artificial Intelligence (N = 100)*

Knowledge Level	Frequency (n)	Percentage (%)
Very knowledgeable	7	7.0%
Somewhat knowledgeable	56	56.0%
Not knowledgeable	19	19.0%
No prior knowledge	18	18.0%
Total	100	100.0%

While 56.0% (n = 56) of the participants identified as "somewhat knowledgeable" regarding medical AI, a substantial combined proportion of 37.0% acknowledged significant knowledge deficits (19.0% "not knowledgeable" and 18.0% "no prior knowledge"). Only 7.0% (n = 7) claimed advanced familiarity ("very knowledgeable"). This distribution indicates a moderate baseline awareness coupled with notable educational gaps, underscoring the necessity for structured health informatics training prior to institutional AI deployment.

Diagnostic Ambiguity Encounter History

The frequency of encountering ambiguous or unclear medical diagnostic outcomes during clinical practice was recorded.

Table 7: *Personal or Professional History of Encountering Unclear Medical Diagnoses (N = 100)*

Encounter History	Frequency (n)	Percentage (%)
Yes	36	36.0%
No	64	64.0%
Total	100	100.0%

Over one-third of respondents (36.0%, n = 36) acknowledged prior exposure to unclear or ambiguous medical diagnoses. Although the majority (64.0%, n = 64) reported no direct encounters with diagnostic ambiguity, the presence of a substantial minority with such experiences highlights real-world analytical gray zones, serving as a potential driver for adopting algorithmic assistance to minimize clinical diagnostic uncertainty.

Trust in AI Diagnostic Accuracy

Professional attitudes concerning the reliability and accuracy of AI algorithms in interpreting test results were measured.

Table 8: *Attitudes and Trust Toward AI-Driven Diagnostic Accuracy (N = 100)*

Perception Category	Frequency (n)	Percentage (%)
No, I do not trust its accuracy	49	49.0%
Unsure, need more evidence	16	16.0%
Concerned about bias/unreliability	16	16.0%
Yes, I trust its accuracy	14	14.0%
Open to trying it	5	5.0%
Total	100	100.0%

The empirical data reveal widespread diagnostic skepticism toward AI accuracy. Nearly half of the workforce (49.0%, n = 49) explicitly expressed distrust in standalone AI accuracy, while 16.0% voiced specific concerns regarding algorithmic bias and systemic unreliability. An additional 16.0% remained cautious, requiring further empirical evidence. Conversely, only 14.0% (n = 14) expressed

complete trust in AI outputs. This dominant skepticism underscores that technical staff view AI as a "black-box" technology requiring rigorous validation before acceptance.

Perception of AI Error-Detection Capabilities

The perceived capacity of AI systems to identify analytical errors and interpret data accurately was evaluated.

Table 9: ***Professional Perceptions of AI Capabilities in Error Detection (N = 100)***

Perception Category	Frequency (n)	Percentage (%)
No, cannot interpret data accurately	50	50.0%
Skeptical of its ability with complex data	19	19.0%
Unsure	14	14.0%
Yes, can detect errors	11	11.0%
Definitely helps prevent errors	6	6.0%
Total	100	100.0%

Exactly 50.0% (n = 50) of respondents doubted AI's ability to interpret laboratory data accurately, with a further 19.0% (n = 19) expressing explicit skepticism regarding its performance on complex, multi-parametric datasets. Only 11.0% (n = 11) affirmed its error-detection capacity, and 6.0% (n = 6) acknowledged its error-prevention potential. These findings illustrate deep reservations regarding algorithmic competence in post-analytical verification without human oversight.

Confidence in AI Handling Complex Data

Confidence levels regarding AI's ability to process and interpret complex biological data were recorded.

Table 10: ***Level of Confidence in AI Processing Complex Diagnostic Datasets (N = 100)***

Confidence Level	Frequency (n)	Percentage (%)
Somewhat confident	39	39.0%
Neutral	29	29.0%
Not confident at all	15	15.0%
Very confident	10	10.0%
Not confident	7	7.0%
Total	100	100.0%

Confidence in AI handling complex diagnostic data was primarily moderate to neutral, with 39.0% (n = 39) reporting being "somewhat confident" and 29.0% (n = 29) adopting a neutral stance. A combined 22.0% expressed limited or no confidence (15.0% "not confident at all" and 7.0% "not confident"), while only 10.0% (n = 10) reported strong confidence. This balanced yet cautious perspective reflects a willingness to acknowledge computational power alongside hesitation toward fully autonomous interpretation.

Likelihood of Recommending AI Integration

The professional willingness of laboratory technicians to recommend deploying AI decision-support tools was surveyed.

Table 11: ***Willingness to Recommend AI Implementation in Result Interpretation (N = 100)***

Recommendation Likelihood	Frequency (n)	Percentage (%)
Neutral / Undecided	40	40.0%
Somewhat likely	31	31.0%
Very likely	11	11.0%
Very unlikely	11	11.0%

Somewhat unlikely	7	7.0%
Total	100	100.0%

Professional endorsement of AI integration is dominated by neutrality and indecision (40.0%, n = 40). While a combined 42.0% expressed positive inclination (31.0% "somewhat likely" and 11.0% "very likely"), 18.0% registered active reluctance (11.0% "very unlikely" and 7.0% "somewhat unlikely"). This dominant neutrality indicates an open but cautious workforce that awaits clear operational protocols, governance, and evidence of clinical utility before committing to endorsement.

3.3.Inferential Statistics: Association and Correlation Analyses

Educational Attainment vs. Diagnostic Self-Efficacy

A Pearson *Chi-Square* test of independence was performed to assess whether academic qualifications significantly influence manual result interpretation confidence.

Table 12: ***Crosstabulation of Educational Qualification and Diagnostic Confidence (N = 100)***

Educational Qualification	Always Confident	Sometimes Confident	Not Confident	Uncertain	Total (n)
Higher Diploma	14 (35.0%)	23 (57.5%)	1 (2.5%)	2 (5.0%)	40
Bachelor's Degree	12 (25.0%)	35 (72.9%)	1 (2.1%)	0 (0.0%)	48
Master's Degree	2 (25.0%)	6 (75.0%)	0 (0.0%)	0 (0.0%)	8
Doctorate (Ph.D.)	1 (50.0%)	1 (50.0%)	0 (0.0%)	0 (0.0%)	2
Other	1 (50.0%)	1 (50.0%)	0 (0.0%)	0 (0.0%)	2
Total	30 (30.0%)	66 (66.0%)	2 (2.0%)	2 (2.0%)	100

Note: Pearson Chi-Square = 5.664, degrees of freedom (df) = 12, p = 0.932 (Not Significant).

The *Chi-Square* analysis revealed no statistically significant association between academic qualifications and confidence in interpreting laboratory results (*Chi-Square* = 5.664, *p* = 0.932). Across all academic levels, the majority of technicians reported being "sometimes confident" (e.g., 72.9% among Bachelor's degree holders and 57.5% among Higher Diploma holders). This outcome demonstrates that formal academic credentials alone do not dictate practical diagnostic self-efficacy in clinical laboratory settings.

Professional Experience vs. Diagnostic Self-Efficacy

The association between cumulative years of laboratory practice and manual result interpretation confidence was evaluated.

Table 13: ***Crosstabulation of Practical Experience Tenure and Diagnostic Confidence (N = 100)***

Experience Tenure	Always Confident	Sometimes Confident	Not Confident	Uncertain	Total (n)
Less than 1 year	1 (7.7%)	12 (92.3%)	0 (0.0%)	0 (0.0%)	13
1–3 years	6 (21.4%)	19 (67.9%)	2 (7.1%)	1 (3.6%)	28
4–6 years	8 (38.1%)	13 (61.9%)	0 (0.0%)	0 (0.0%)	21
7–10 years	5 (35.7%)	9 (64.3%)	0 (0.0%)	0 (0.0%)	14
More than 10 years	10 (41.7%)	13 (54.2%)	0 (0.0%)	1 (4.2%)	24
Total	30 (30.0%)	66 (66.0%)	2 (2.0%)	2 (2.0%)	100

Note: Pearson Chi-Square = 13.501, df = 12, p = 0.334 (Not Significant); Linear-by-Linear Association = 3.472, p = 0.062 (Borderline).

Although overall Chi-Square testing did not reach statistical significance (*Chi-Square* = 13.501, *p* = 0.334), a clear descriptive trend is observable: technicians with >10 years of experience exhibited the highest rate of consistent confidence (41.7%), whereas 92.3% of entry-level technicians (<1

year) reported being only "sometimes confident." The linear-by-linear association test approached statistical significance ($p = 0.062$), suggesting a potential positive directional relationship between accumulated clinical tenure and diagnostic self-assurance that may achieve significance in larger sample sizes.

Experience Tenure vs. Confidence in AI Processing Complex Data

A Pearson correlation analysis was conducted to quantify the relationship between professional experience and trust in AI's analytical capabilities.

Table 14: ***Pearson Correlation Between Experience Tenure and Confidence in AI Complex Data Processing***

Variable Pair	Pearson Correlation (r)	Significance (p-value, 2-tailed)	Sample Size (N)
Years of Laboratory Experience × Confidence in AI Interpreting Complex Data	0.225*	0.025	100

** Correlation is statistically significant at the 0.05 level (2-tailed).*

4- Discussion

Bivariate correlation analysis demonstrated a statistically significant positive correlation between cumulative laboratory experience and confidence in AI's ability to interpret complex diagnostic data ($r = 0.225$, $p = 0.025$). Although the correlation strength is modest, this finding indicates that senior, experienced technicians possess higher trust in AI's computational capacity to handle intricate biological datasets, likely because their extensive exposure to complex cases enhances their appreciation for computational decision support.

This empirical investigation evaluated baseline technological literacy, diagnostic trust, and professional attitudes among medical laboratory personnel regarding the integration of artificial intelligence (AI) in clinical test interpretation across selected diagnostic facilities in Northwestern Libya. The structural composition of the analyzed workforce—predominantly deployed across public government hospitals (50.0%) and independent private diagnostic laboratories (34.0%), with a primary foundation of Bachelor's degree (48.0%) and Higher Diploma (40.0%) qualifications—reflects the operational reality of clinical diagnostic delivery in developing healthcare ecosystems [1, 2].

Regarding baseline digital literacy, the descriptive analysis revealed that while 56.0% of laboratory technicians self-identified as "somewhat knowledgeable" concerning healthcare AI applications, a substantial cumulative fraction of 37.0% acknowledged profound knowledge deficits, reporting minimal or absolute lack of prior exposure [3]. This moderate-to-low level of domain familiarity aligns closely with global evaluations by Rajpurkar *et al.* [1] and Ahmed *et al.* [3], who emphasized that the scarcity of formal health informatics education remains a formidable barrier hindering the seamless assimilation of algorithmic decision support into routine laboratory workflows. As highlighted by Shortliffe and Sepúlveda [10] as well as Kaul *et al.* [11], foundational cognitive gaps in medical informatics frequently lead to either unwarranted automation reliance or profound professional skepticism during diagnostic evaluation.

Indeed, the empirical findings of this study uncovered deep-seated diagnostic skepticism among the technical staff: 49.0% of participants expressed explicit distrust in the standalone accuracy of AI systems, and 50.0% voiced direct doubt regarding the autonomous capacity of algorithms to interpret complex biological datasets or detect analytical errors [3, 4]. These cautious attitudes converge strongly with the conclusions of Bera *et al.* [7] and Ardon and Schmidt [4], who documented that non-transparent "black-box" computational models induce considerable professional hesitation among diagnostic specialists when evaluating multi-parametric clinical data. Furthermore, the explicit concerns regarding systemic unreliability and algorithmic bias articulated by 16.0% of respondents reinforce the warnings raised by Char *et al.* [12] and Parikh *et al.* [14], indicating that unvalidated training datasets can introduce latent biases that compromise clinical diagnostic safety.

When evaluating the determinants of technology acceptance, inferential evaluation demonstrated no statistically significant association between a practitioner's academic qualification tier and their self-efficacy in manual result interpretation ($p = 0.932$) [3]. This statistical outcome indicates that formal academic degree tiering alone does not inherently dictate practical diagnostic confidence under routine laboratory conditions [8, 15]. Conversely, bivariate correlation analysis demonstrated a

statistically significant positive relationship between cumulative practical laboratory experience and heightened confidence in AI's capability to process complex diagnostic datasets ($r=0.225$, $p=0.025$) [3].

This key empirical outcome strongly supports the paradigm of human-machine synergy articulated by Topol [5] and Esteva *et al.* [8], wherein seasoned diagnostic professionals utilize their accumulated domain expertise to conceptualize computational intelligence not as an occupational threat, but as an indispensable cognitive assistant that mitigates human analytical fatigue. This observation is corroborated by Scopus-indexed investigations by Naugler and Church [6] as well as D'Urso *et al.* [2], both of which highlighted that senior technical personnel—routinely exposed to high sample volumes and complex analytical gray zones—exhibit a pragmatic appreciation for automated data-curation tools capable of streamlining pre-analytical and post-analytical error detection.

Despite acknowledging computational utility, overall professional sentiment remains markedly conservative, as evidenced by the 40.0% neutrality and indecision rate regarding the active recommendation of AI implementation in clinical result interpretation [3]. This institutional and psychological hesitation reflects well-documented regulatory and ethical hurdles within emerging healthcare infrastructures [9, 12]. As argued by Goddard *et al.* [13] and Price *et al.* [15], full technological adoption in high-stakes clinical laboratory settings necessitates rigorous prospective validation, transparent algorithmic audit trails, and explicit legal governance that firmly preserves human signatory authority within the analytical loop ("Human-in-the-Loop" architecture). Without clear operational guidelines and ethical framework enforcement, laboratory professionals naturally default to risk-averse neutrality to safeguard patient outcomes and mitigate legal liability [9, 15].

5- Conclusion

This study evaluated the readiness and professional attitudes of medical laboratory personnel regarding AI deployment in Northwestern Libya. The core conclusions are:

- **Training Gaps:** Operational awareness of AI remains limited by the absence of health informatics in current biomedical curricula.
- **Diagnostic Skepticism:** Algorithmic non-transparency ("black-box" nature) fosters widespread caution and skepticism toward standalone automated accuracy.
- **Experience vs. Credentials:** Diagnostic self-efficacy and AI trust are driven by cumulative clinical tenure rather than formal degree levels, with senior technicians showing greater receptivity to reduce analytical fatigue.
- **Human Oversight:** AI is strictly perceived as a supportive decision-aid; full clinical adoption remains dependent on preserving human verification and final signatory authority.

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