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ORIGINAL ARTICLE

Perception of Medical Laboratory Professionals on the Role of Artificial Intelligence in Advancing Hematology Diagnostics

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ABSTRACT

Background: **Artificial Intelligence (AI) has grown quickly in healthcare and has had a big effect on medical laboratory diagnostics, especially when it comes to diagnosing blood disorders. To figure out the pros and cons of using AI in hematology diagnostics, it is important to understand the perspective of medical laboratory workers instead of specialists toward AI use in hematology laboratory diagnostics. The goal of this study was to investigate what medical lab workers now know about AI and how they think it affects the accuracy of diagnostic hematology and patient outcomes.**

Methods: **Methods involved 113 participants, mostly laboratory technologists who filled out a standardized questionnaire as part of a quantitative exploratory research design. The data collection phase lasted 6 months, during which time-informed consent was sought and reminders were provided to boost response rates. Statistical tests were used including *t*-tests and regression analysis to determine the links between demographic factors and workers' opinions on AI in hematological diagnoses.**

Results: **The primary findings of this study dwell within the role of job skill and gender influence on "attitude", specifically, the study found that most of the participants believe that their professional attitude to adoption of AI in diagnoses could make their job more accurate and faster. However, there were several concerns about the quality of data, how easy it will be to understand the model, and the moral implications. There were positive relationships between knowledge, attitudes, and practices linked to AI. The secondary outcomes showed that most of the participants were young, with 45.1% being between the ages of 30 and 39. In addition, 65.5% of them had bachelor's degree, which suggests that they were comfortable with technology. Some of the participants had less than ten years of work experience, while others had more than ten years. Statistical tests demonstrated that demographic characteristics are quite important in how medical laboratory workers think about AI.**

Conclusions: **Medical laboratory workers believe that the use of AI in hematology diagnostics has its benefits, but they need more training and assistance to deal with their fears and create a space where human expertise and AI technologies can work together. By taking these views into account, healthcare organizations may better educate their staff for the changing role of AI in diagnostics, which will lead to improved patient outcomes and satisfaction.**

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INTRODUCTION

The fast growth of artificial intelligence (AI) in healthcare has had a big effect on medical laboratory diagnostic, especially when it comes to diagnosing blood diseases. AI and related technologies could make diagnoses more accurate, make the lab work easier, and improve patient outcomes, notably in hematological diagnosis. As the sector changes, it is more vital than ever to understand what medical laboratory workers think, because their opinions can show both the benefits and possible concerns about using AI-driven solutions in clinical practice [1]. AI is becoming more and more well-known for how it could change hematology diagnostics by making them more accurate, faster, and better at making decisions. AI technologies, especially machine learning and deep learning, make it possible to look at complicated data patterns from genomic, cytogenetic, and morphological datasets. This considerably improves the accuracy and consistency of hematological diagnoses [2].

There are several ways to look at AI in relation to how medical laboratory workers see hematological diagnostics. That is, there are a lot of different points that can affect AI, for example, "Diagnostic Accuracy", "Operational Efficiency", "Ethical & Regulatory", "Implementation Challenges", and "Human-AI Augmentation". Even while AI has some promising benefits, studies show that many experts are quite worried about its use, even though they agree that it might make diagnosis more accurate and faster. These include issues with the quality of data, how easy it is to understand the model, and moral difficulties such as patient privacy and being responsible for decisions [3] Also, there are concerns about job security and the possibility that patient care would become less human, which could make lab workers less likely to fully accept and trust AI technologies [4]. Laboratory automation, such as AI-powered analyzers, has also made big advances in important operational measures including turnaround time, reducing errors, and managing workloads. A recent study that looked at different hospital laboratories using a comparative observational methodology found that adding AI to the labs made them much more accurate and efficient [5].

Significant advances and challenges in applying artificial intelligence to laboratory hematology as emphasized by Liao et al. [6] dwell on integrating multimodal numerical and imaging data to enhance diagnostic performance but require robust dataset diversity, regulatory compliance, and explainable modeling [6]. While AI is reshaping hematology by improving accuracy and reducing manual workloads, validation and ethical safeguards remain essential. To successfully use AI in hematological diagnostics, it is important to solve these issues through targeted educational programs that teach medical laboratory workers about AI and encourage them to work together. Training programs should focus on both the technical skills needed to employ AI in therapeutic settings and the moral issues that come up when using AI. To get the most out of AI while minimizing its risks, we need to keep doing research, have healthcare providers and AI professionals work together, and create complete regulatory frameworks. Institutions can help make the shift to AI-enhanced diagnostics easier for laboratory personnel by identifying and resolving their worries and views. This will make sure that these new technologies lead to real benefits in patient outcomes [7]. The creation of machine learning-based Clinical Decision Support Systems (CDSS) has also made it possible for regular lab data, including complete blood counts (CBC), coagulation profile and related tests, and biochemical test panels, to be used more in predicting and diagnosing hematological diseases. Models like random forest and XGBoost have been quite accurate and easy to understand. They have helped with personalized treatment and proven how important it is for medical technologists to provide high-quality data [8].

This current study intends to achieve the following objectives:

- To find out what medical laboratory workers think about how AI affects the accuracy and speed of hematological diagnoses.
- To investigate how the knowledge, attitudes, and behaviors of medical laboratory (workers) instead of experts affect their willingness to use AI in hematology laboratory.
- To find the main problems and worries that affect how well AI technologies are accepted and used in clinical labs, like data quality, ethical issues, and how easy it is to understand the models.
- To look into how demographic parameters like age, education level, and work experience affect how ready and comfortable professionals are with using AI-based diagnostic tools.
- To provide ways for institutions to teach and assist their staff so that they can work well with AI and be ready for work in hematological diagnostics.

  In light of the larger picture of incorporating AI into clinical workflows and the need for enabling infrastructure in medical labs, the study's main contributions are as follows:

- The study gives real-world proof of how medical laboratory workers see the effects of AI on hematological diagnoses. It shows that they strongly believe it can improve accuracy and efficiency.
- The study finds a strong positive relationship between professionals' knowledge, attitudes, and practices toward AI, which means that more knowledge leads to more positive adoption behaviors.
- The results show that ongoing training and institutional support are necessary to address concerns about data quality, ethical implications, and model interpretability. This information can be used to help prepare the diagnostic workforce for AI integration.

The current study found that knowledge, attitude, and behaviors are the main things that affect AI's impact on hematological diagnoses. But it might not be true because AI does not have a theoretical basis, and it might be too much. With that said, most medical lab personnel think that AI will make hematological testing more accurate and faster. However, problems in implementation need to be fixed before it can reach its full potential. AI is great at making diagnoses more accurate and operations run more smoothly, but stakeholders and decision-makers should focus on getting over these transitional problems first. This study looked at a lot of different sources to find important results and future prospects in the field of AI and how medical laboratory personnel understand it in the context of hematological diagnostics.

Before directly getting to AI implementation in hematology, there is a need to identify some of the classes of automated hematology analyzers studies [6,9-13]. Tests of neutrophil percentages obtained from automated hematology analyzers show a strong and favorable correlation of microscopic examination in malignant lymphoma patients receiving chemotherapy [9]. Hence the application of automated approach yielded an accurate therapy-induced hematologic fluctuation and effectively reduced manual workload while maintaining diagnostic reliability. With this, it is now possible to routinely apply automated differential counts in the field of hematology, while microscopy is reserved for patients who are nearing a diagnosis. Similarly, automated hematology analyzers play a critical role in detecting and monitoring neutropenia, particularly in individuals with inherited blood disorders. The discussion highlights their ability to provide rapid and accurate neutrophil quantification but also stresses the necessity of interpreting analyzer flags within clinical context, given the potential for morphological abnormalities to affect automated outputs. Enhanced integration of automation and clinical oversight is essential for effective patient management in neutropenic conditions [10]. Similarly, commercial automated blood cell analyzers showed promising agreement for several hematological parameters in rainbow trout samples [11]. This highlights the need for algorithm adjustment and calibration when applying automated hematology tools.

Tayebi et al. [14] built a deep learning-based system for automated bone marrow cytology. It used a new "Histogram of Cell Types" to accurately classify cells. This approach was quite good at finding and sorting bone marrow cells, and it also reduced the differences between observers [14]. In a related breakthrough, Shu et al. [15] created an AI-powered imaging hematology analyzer that does not need any reagents and can sort leukocyte subpopulations using label-free images. Their results showed that they could classify cells very well, especially when it came to telling the difference between B and T lymphocytes [15]. This means that they could be very useful in hospital settings when resources are limited.

A recent study looked at how artificial intelligence (AI) can improve patient care and hospital operations. Their results showed that the integration of artificial Intelligence technologies clearly improved operational efficiency as well as patient outcomes [16]. Kriger [17] did a cross-disciplinary study of AI applications in medicine and discovered that AI not only improved continuity of care and allowed for early intervention, but it also made it easier for everyone to get good diagnostics [17]. Evaluating the use of artificial intelligence in clinical decision support systems and healthcare delivery was carried by Ouanes and Farhah [18]. In clinical settings, their research revealed considerable increases in general operational efficiency and diagnosis accuracy. Another recent study investigated how artificial intelligence technology might enhance mental health unit patient flow [19]. The study underlined improved operational efficiency arising from successful applications in cost control, staff scheduling, and predictive modeling [19]. Emphasizing the requirement of justice, responsibility, and openness, Li et al. [20] systematically reviewed ethical concerns around artificial intelligence in healthcare. Their findings highlight how urgently ethical frameworks must be put into effect to reduce bias [20]. By means of clinical case scenarios, Goktas and Grzybowski [21] investigated how ethical issues in artificial intelligence affect patient outcomes and workflow. Their results underlined how trustworthy healthcare systems depend on integrating AI deployment with ethical values [21]. In addition, another study was performed in a scoping assessment on the ethical and social aspects of AI in healthcare. It found big gaps in the frameworks that are now in place and stressed the need for continual evaluation as AI systems change [22]. Hanna et al. [23] tackled ethical issues in artificial intelligence and machine learning applications inside pathology as well as bias. Their results begged questions about data representativeness, algorithm openness, and public confidence in artificial intelligence systems [23].

Interpretive Structural Modeling (ISM) was used to examine and structure eleven healthcare AI implementation difficulties [24]. ISM assessed challenge interrelationships, reliance, and driving power. A 5-tiered hierarchical model was created. Innovation and new tools were the biggest obstacle. Insufficient data, data acquisition, data misuse, and missing compassion were the biggest obstacles. These are fundamental concerns that must be addressed for AI integration. The findings show that data-related and innovation difficulties are key to healthcare AI adoption [24]. Another study looked at structural and data-related problems with AI adoption. The research underlined the need to adapt AI solutions to particular application settings and tackling problems connected to data integration and relevancy [25]. A comprehensive thematic analysis of healthcare AI implementation obstacles and promise was undertaken [26]. The investigation highlighted several major issues, including problems integrating clinical workflows and found many AI benefits despite obstacles, including better diagnostic and decision-making to improve patient care and healthcare systems. Albahri et al. [27] re-

viewed reliable and understandable artificial Intelligence in healthcare holistically. They found as ongoing challenges to AI adoption data quality, model interpretability, and bias hazards.
Tien [28] examined how real-time artificial intelligence decision-making improves medical treatment personalization, particularly in difficult disciplines like oncology. Their results confirmed the value of artificial intelligence in customizing treatments to patient-specific circumstances and reactions. Another work made by Maadi et al. [29], reviewing more than 100 cases on human-AI contact, highlighted the requirement of precise job definition since their findings showed that hybrid systems do not always outperform stand-alone human or artificial intelligence decision-makers [29]. The success elements and difficulties in AI-supported healthcare decision-making were studied previously and the indispensable need of human contextual awareness as well as the benefits of artificial intelligence in data-driven activities were proven to be important elements [30]. By classifying degrees of human-AI collaboration, Raees et al. [31] advanced this conversation. Their study shows that many systems fall short of ideal interface design, hence more interactive and explainable artificial intelligence solutions are needed [31]. Even while there is more evidence that AI could improve the accuracy of diagnoses and the efficiency of operations in hematology, there is still a big gap in research when it comes to putting these findings into a strong theoretical framework. Like many other studies, this study investigates the patterns in knowledge, attitudes, and behaviors, but it does not have a conceptual model to show how these pillars work together to affect how medical laboratory personnel use AI. Also, previous studies have looked upon technological capabilities and ethical issues but not much has been said about the social and professional factors that affect how people embrace and trust AI systems. In real life, there are still a lot of issues that have not been fully investigated, like skill degradation, data quality, model interpretability, and ambiguous roles for humans and AI.

MATERIALS AND METHODS

A quantitative, cross-sectional questionnaire was conducted to assess the knowledge, attitudes, and practices (KAP) of medical laboratory workers regarding the use of AI in diagnosing blood disorders. The questionnaire allowed for the systematic collection of structured answers, which made it possible to quantify KAP related to AI technology in hematology laboratories. The reason for using this method is that it can give a clear picture of how different factors are related without having to follow up over time [32]. Questionnaires with closed-ended questions are considered a helpful tool since it gives real-world knowledge about how medical laboratory professionals utilize and see AI-powered diagnostic technology. Ethical approval was obtained from the research and ethic committee, Faculty of Applied Medical Sciences at King Abdulaziz University with reference number (FAMS-EC2024-06). All participants were informed and consented before answering the questionnaire.

Target population of the study

The study focused on a certain group of medical laboratory workers who work in hematology laboratory. The group was classified based on demographic data including gender, age, educational background, marital status, professional responsibility, and years of work experience. This gave a wide range of views on how ready hematology laboratory personnel are for AI and how they feel about it in clinical laboratory settings. The categorization of medical laboratory workers involved in hematological diagnostic services comprised staff in different positions including laboratory technologists, senior laboratory technologists, laboratory technicians, and hematopathologists. Inclusion criteria included workers with a wide range of professional experience, educational background, and demographic traits, which made sure that everyone had a full understanding of the topic. There were 113 workers who filled out the structured questionnaire correctly. Finding the right sample size is very important in descriptive quantitative research to make sure the study's results are valid and reliable. Mursa et al. [33] concluded that there is no one-size-fits-all way to figure out the sample size for descriptive studies. However, factors including the study's goals, the population's diversity, and limited resources are very important [33].
For exploratory research to find patterns and connections in a certain group of respondents, a sample size of 113 was adequate.

Instrument for data collections

This study collected data using a structured, self-administered questionnaire. This questionnaire was specifically developed to gather critical data on how medical laboratory personnel use AI in hematological diagnosis. The questionnaire used three Knowledge-Attitude-Practice (KAP) concepts: Knowledge, which assessed participants' understanding of how AI might increase diagnosis accuracy. Attitude encompasses medical lab workers' views on ethics, data protection, AI integration, and care becoming less human. Practice – examining how AI is used or supported in diagnostic workflows, its benefits, and its drawbacks in clinical laboratories. In addition to KAP characteristics, the questionnaire contained personal information such as gender, age, degree, job role, marital status, and years of experience. Closed-ended questions on a 5-point Likert scale made it easier to collect consistent replies and excellent statistical analysis. The instrument was developed after a thorough literature review and expert interviews [7, 34]. This ensured that the content was accurate and consistent with healthcare AI adoption research. Alanzi et al. [7] and Memon et al. [34] have successfully mea-

sured preparedness and attitudes toward AI in clinical diagnostics using a similar structured questionnaire, proving the method's validity [7,34].
A small group of clinical laboratory professionals (not in the final sample) pilot-tested the questionnaire to ensure its clarity, reliability, and consistency. To verify results, Cronbach's Alpha was employed to assess internal consistency.

Analytical flow
To make sure the results were accurate, clear, and thorough, the data analysis for this study followed a disciplined, multi-phase procedure. In the first step, data cleaning and validation took place including checking the responses for completeness, consistency, and outliers to make the dataset more reliable. This step is very important to lower bias and protect the accuracy of statistical analysis [34]. After validation, descriptive statistics were used to summarize demographic information and give a basic picture of how participants responded to the knowledge, attitude, and practice (KAP) conceptions about AI in hematological diagnostics [32]. Then, inferential statistical approaches including independent samples *t*-tests and regression analyses were utilized to examine the links between demographic data and the KAP factors. These tests made it possible to find statistically significant differences and links, which is what is done in cross-sectional healthcare studies [37]. Finally, the results were compared to what is already known about using AI in healthcare, especially in lab diagnostics, to put them in context and show how they can affect practice and policy.

RESULTS

Descriptive and inferential analysis was performed to test the stated hypothesis (Demographic factors significantly influence the knowledge, attitude, and practice (KAP) of medical laboratory workers regarding the use of AI in diagnostic hematology laboratories). Descriptive statistics were used to give an overview of the demographics and general response patterns, which helped us understand the participants and the distribution of critical variables [32]. After that, inferential statistical approaches including independent samples *t*-tests and regression analysis were used to look at the differences and correlations between KAP variables and demographic groupings. This is the hypotheses testing and looking for connections in the dataset, which make generalizations about the population being studied [33]. Using both descriptive and inferential analyses are in line with best practices in healthcare and technology adoption research since it gives a broader and deeper understanding of empirical data [7]. The results are shown through tables and narrative interpretations to make sure they are clear and to show important trends, connections, and implications for the use of AI in diagnostic labs [34].

The study obtained a total of 113 participants who filled out the structured questionnaire completely. This response rate was sufficient to do both descriptive and inferential statistical analysis, which made it possible to find relevant patterns and connections in the data set (Table 1). 31.9% of the participants that answered were women, which means that women were moderately represented in the sample. Even if the gender balance isn't perfect, this distribution shows the gender diversity that is common in clinical laboratory settings, where both men and women work.
Most participants who answered the questionnaire were between the ages of 30 and 39 (45.1%), followed closely by those between the ages of 20 and 29 (42.5%). This means that most of the participants in the sample were professionals in the early to middle stages of their careers, which means they were probably both tech-savvy and open to new technologies like AI. The 40 – 49 years (10.6%) and 50 years and over (1.8%) groups had smaller numbers, which means there were not many elderly professionals. The educational backgrounds of the participants that answered show that they are well qualified. 65.5% had a bachelor's degree, which is usually the least amount of education needed to work in a lab. Also, 26.5% of them had a master's degree and 8.0% had a PhD. This shows that they had a good intellectual background and could think critically about new technologies like AI in diagnostics. In terms of marital status, 50.4% of the participants who answered were single, 46.9% were married, and 2.7% were divorced. This fairly even distribution gives the demographic profile more depth by showing how marital status can occasionally affect work-life balance and willingness to learn new skills or adapt to new technologies.
The study showed that having a higher degree of education did not significantly predict AI knowledge ratings. Participants with a master's degree showed a small gain ($\beta = 0.60$, $p = 0.629$), while participants with a PhD had a lower score ($\beta = -4.11$, $p = 0.146$) than participants with a bachelor's degree. Marital status also did not have a big effect; single ($\beta = 4.11$, $p = 0.266$) and married participants scored the same as divorced participants ($\beta = -0.08$, $p = 0.981$). The job variable had a big impact; senior laboratory technologists scored much higher than laboratory technicians ($\beta = 5.12$, $p = 0.014$). This suggests that having more experience and responsibility may help workers learn more about AI. Laboratory technologists and pathologists also did better, although not by a lot. Workers with 1 - 5 years, 6 - 10 years, or more than 10 years of work experience were not statistically different from interns. Overall, the results show that gender and work role have a bigger impact on AI understanding than education or experience. This shows how important it is to give focused training, especially to women and junior personnel, to help make sure that AI is used fairly in hematology labs. As a result, this is one of the primary outcomes of the research. This finding is also supported by Cachero et al. of gender influences on AI self-perception [35].

Table 1. Demographic characteristics of study participants.

Criteria	n = 113 (%)
Gender (%)	
Female	36 (31.9)
Male	77 (68.1)
Age (%)	
20 - 29 years	48 (42.5)
30 - 39 years	51 (45.1)
40 - 49 years	12 (10.6)
50 and above	2 (1.8)
Education (%)	
Bachelor’s degree	74 (65.5)
Master’s degree	30 (26.5)
Doctorate (PhD)	9 (8.0)
Marital status (%)	
Divorced	3 (2.7)
Single	57 (50.4)
Married	53 (46.9)
Job role (%)	
Senior laboratory technologist	11 (9.7)
Laboratory technologist	84 (74.3)
Laboratory technician	15 (13.3)
Pathologist/hematopathologist	3 (2.7)
Work experience (%)	
Less than 1 year - (intern)	23 (20.4)
1 - 5 years	30 (26.5)
6 - 10 years	38 (33.6)
more than 10 years	22 (19.5)

Table 2. Descriptive statistics of knowledge, attitude, and practice (KAP) scores.

	Attitude score	Knowledge score	Practice score
n	113	113	113
Median	35	34	35
Shapiro-wilk	0.002	< 0.001	< 0.001
25th percentile	33.0	31.0	32.0
75th percentile	37.0	39.0	39.0

Table 3. Correlation among knowledge, attitude, and practice scores.

		Attitude score	Knowledge score
Knowledge score	Spearman's rho	0.722	-
	p-value	< 0.001	-
Practice score	Spearman's rho	0.734	0.886
	p-value	< 0.001	< 0.001

Table 4. Multiple regression analysis for predictors of knowledge score.

Predictor	Estimate	SE	T	p
Intercept [a]	26.6358	3.97	6.7170	< 0.001
Gender				
Male - female	2.6493	1.12	2.3590	0.020
Age				
30 - 39 years – 20 - 29 years	2.0439	1.32	1.5514	0.124
40 - 49 years – 20 - 29 years	1.9976	2.64	0.7580	0.450
50 and above – 20 - 29 years	7.3266	3.94	1.8603	0.066
Education				
Master's degree - bachelor's degree	0.5981	1.24	0.4840	0.629
Doctorate (PhD) - bachelor's degree	-4.1079	2.80	-1.4666	0.146
Marital status				
Single - divorced	4.1099	3.68	1.1181	0.266
Married - divorced	-0.0818	3.45	-0.0237	0.981
Job role				
Senior laboratory technologist - laboratory technician	5.1185	2.04	2.5143	0.014
Laboratory technologist - laboratory technician	2.2100	1.48	1.4923	0.139
Pathologist/hematopathologist - laboratory technician	3.1611	3.85	0.8202	0.414
Work experience				
1 - 5 years - less than 1 year - (intern)	0.2267	1.65	0.1371	0.891
6 - 10 years - less than 1 year - (intern)	0.8347	2.23	0.3736	0.710
More than 10 years - less than 1 year - (intern)	-0.6616	2.63	-0.2512	0.802

Table 5. Multiple regression analysis for predictors of attitude score.

Predictor	Estimate	SE	T	p
Intercept [a]	34.8150	3.067	11.35165	< 0.001
Gender				
Male - female	1.9379	0.869	2.23104	0.028
Age				
30 - 39 years - 20 - 29 years	1.6437	1.019	1.61311	0.110
40 - 49 years - 20 - 29 years	-0.4111	2.038	-0.20170	0.841
50 and above - 20 - 29 years	-0.2823	3.046	-0.09269	0.926
Education				
Master's degree - bachelor's degree	0.1062	0.956	0.11112	0.912
Doctorate (PhD) - bachelor's degree	-0.6299	2.166	-0.29076	0.772
Marital status				
Single - divorced	-1.8269	2.843	-0.64263	0.522
Married - divorced	-4.8257	2.671	-1.80683	0.074
Job role				
Senior laboratory technologist - laboratory technician	3.9392	1.575	2.50181	0.014
Laboratory technologist - laboratory technician	2.0924	1.145	1.82674	0.071
Pathologist/hematopathologist - laboratory technician	3.4180	2.981	1.14670	0.254
Work experience				
1 - 5 years - less than 1 year - (intern)	-0.9728	1.278	-0.76099	0.448
6 - 10 years - less than 1 year - (intern)	0.0118	1.728	0.00683	0.995
more than 10 years - less than 1 year - (intern)	-2.0851	2.037	-1.02373	0.308

Table 6. Multiple regression analysis for predictors of practice score.

Predictor	Estimate	SE	t	p
Intercept [a]	31.446	3.425	9.1809	< 0.001
Gender				
Male - female	2.837	0.970	2.9249	0.004
Age				
30 - 39 years - 20 - 29 years	4.174	1.138	3.6677	< 0.001
40 - 49 years - 20 - 29 years	2.591	2.276	1.1383	0.258
50 and above - 20 - 29 years	10.010	3.402	2.9424	0.004
Education				
Master's degree - bachelor's degree	0.580	1.067	0.5439	0.588
Doctorate (PhD) - bachelor's degree	-1.088	2.419	-0.4498	0.654
Marital status				
Single - divorced	-0.136	3.175	-0.0429	0.966
Married - divorced	-3.537	2.983	-1.1859	0.239
Job role				
Senior laboratory technologist - laboratory technician	4.540	1.758	2.5816	0.011
Laboratory technologist - laboratory technician	3.347	1.279	2.6167	0.010
Pathologist/hematopathologist - laboratory technician	2.187	3.329	0.6571	0.513
Work experience				
1 - 5 years - less than 1 year - (intern)	-2.293	1.428	-1.6059	0.112
6 - 10 years - less than 1 year - (intern)	-2.515	1.930	-1.3033	0.196
more than 10 years - less than 1 year - (intern)	-5.479	2.275	-2.4088	0.018

Different types of professionals in the study sample were investigated. The largest group was laboratory technologists (74.3%), followed by laboratory technicians (13.3%), senior technologists (9.7%), and pathologists/hematopathologists (2.7%). Interns made up 20.4% of the workforce, participants with 1 - 5 years of experience made up 26.5%, participants with 6 - 10 years of experience made up 33.6%, and those with more than 10 years of experience made up 19.5%. This variety made sure that both junior and senior professionals were represented. The demographic profile, which is mostly made up of young, well-educated participants, is perfect for examining AI adoption since professionals in their early and middle careers are more open to new technologies and can shape the future of hematological diagnostics.

The median scores for attitude, knowledge, and practice were 35, 34, and 35. The interquartile range (IQR) for these scores were: Attitude score: (33 - 37), knowledge score: (31 - 39), and practice score: (32 - 39) (Table 2). This study has acknowledged this result to be another primary outcome of the research, where a strong positive relationship between knowledge, attitude, and practice scores was established. For example, Spearman's rho = 0.722, $p < 0.001$. Knowledge and practice scores: Spearman's correlation = 0.886, $p < 0.001$. Spearman's rho for attitude and practice scores is 0.734, and p is less than 0.001. The participants responses across “Attitude” dimension with regards to exploratory direction indicate a high concentration of scores near the top of the median. As a result, this primarily demonstrated that the medical laboratory personnel are enthusiastic about utilizing AI for hematological diagnosis. This is a crucial initial stage for institutions to effectively integrate AI. This means that those who know more are also likely to have better attitudes and practices (Table 3).

This part goes into detail about how the study's main variables - knowledge, attitude, and practice - are related to each other, as stated by medical laboratory workers who employ artificial intelligence (AI) in hematological diagnostics. The goal of this study is to find out how statistically related these variables are and to see how clinical laboratory workers' knowledge and opinions about AI affect how they use AI technologies in laboratory settings. The study used correlation analysis to find out the direction and intensity of the correlations between the KAP components to look into this relationship. Regression analysis was used to examine how well knowledge and attitude variables could predict AI-related practices. These statistical methods are great for looking at how independent variables (like knowledge and attitude) affect the dependent variable (like prac-

tice), especially in healthcare technology studies that use cross-sectional study designs.
The results of this examination of interrelationships are very important for the bigger picture about how AI is being used in medical labs. The results show whether workers who know more about AI have better opinions about it and whether these attitudes lead to more use of AI tools in diagnostic protocols. These insights are very helpful for creating evidence-based solutions, such as tailored training programs, professional development initiatives, and changes to institutional policies that make it easier for AI to be used in hematological diagnosis. Understanding these connections also helps find any gaps, such when someone has a lot of information but does not use it in real life. This shows where more education or organizational support may be needed. The results of the study serve as a strategic roadmap for stakeholders that want to improve the readiness and responsiveness of laboratory personnel to new AI technologies in clinical diagnostics.

Predictors of knowledge score (multiple regression analysis)

A multiple regression study was done to find the demographic and professional parameters that affect how much medical laboratory workers know about using AI in hematological diagnoses (Table 4). The knowledge score was the dependent variable in the model. The independent factors were gender, age, degree of education, marital status, job role, and work experience. The model was statistically significant overall, which means that at least one of the predictors had a real effect on differences in knowledge scores. The model's intercept was 26.64, which showed the reference group's starting knowledge score. This group was made up of women aged 20 to 29 who had a bachelor's degree, were divorced, worked as laboratory technicians, and had less than a year of experience.
Gender was a strong predictor of knowledge. Male participants scored much higher on the knowledge measure than female participants, with a regression coefficient (β) of 2.65 and a p-value of 0.020. This means that, with everything else being equal, males laboratory workers had a knowledge score that was 2.65 points greater than females. This discrepancy between men and women may be because they have had different amounts of AI-related training or are less confident in using digital technologies. The group of people aged 50 and older showed the most gain in knowledge scores compared to the reference group (20 - 29 years), with $\beta = 7.33$. However, this result was not significant ($p = 0.066$). The findings do not prove anything statistically, but they do imply a possible trend: older professionals may know more than younger ones, presumably because they have more experience or have been using new technology for a longer time. Compared to the youngest group, those in other age groups (30 - 39 and 40 - 49 years) had more knowledge, but the differences were not statistically significant.

Predictors of attitude score (Multiple regression analysis)

The multiple regression analysis looked at which factors are the best at predicting how medical laboratory workers feel about using AI in hematological diagnostics (Table 5). The study looked at age, gender, education, marital status, employment role, and work experience. Gender was a statistically significant predictor, with males having more positive views than females ($\beta = 1.94$, $p = 0.028$). Age did not matter; workers aged 30 to 39 ($\beta = 1.64$, $p = 0.110$), 40 to 49 ($\beta = -0.41$, $p = 0.841$), and 50 and older ($\beta = -0.28$, $p = 0.926$) were not significantly different from others aged 20 to 29. Attitude scores were likewise not affected by education level. Master's degree holders ($\beta = 0.11$, $p = 0.912$) and PhD holders ($\beta = -0.63$, $p = 0.772$) had ratings that were quite similar to those of bachelor's degree holders. Marital status also did not have a big effect; single workers ($\beta = -1.83$, $p = 0.522$) and married workers ($\beta = -4.83$, $p = 0.074$) scored about the same as divorced participants. On the other hand, employment factor was a strong predictor: senior laboratory technologists had far higher attitude scores than technicians ($\beta = 3.94$, $p = 0.014$), which suggests that workers in greater-responsibility roles are more open to AI. There was no significant influence of work experience because the differences between all experience groups and interns were not statistically significant. The only important factors that predicted good views toward AI were gender and job role. Exploratory descriptive analysis has already revealed that participants' responses in the "Attitude" dimension exhibit a high score. This basically demonstrates that medical laboratory professionals are willing to utilize AI for hematological diagnosis. Another primary key outcome of the research is the identification of the determinants of "Attitude." It has now been uncovered to be "Job role" as the most significant predictor of "attitude". This follows by "gender" Therefore, the duties of hematological diagnosis with respect to gender exhibit remarkable acceptance of AI adoption. These results show how important it is to create focused training, especially for junior and female workers, to make sure that everyone can use AI in laboratory diagnoses in a fair and inclusive way. Age, education, and experience were not strong factors that affected attitude.

Predictors of practice score (multiple regression analysis)

The multiple regression analysis found important factors that could help predict AI practice scores among medical laboratory professionals. Gender was quite important; men had much higher practice scores than women ($\beta = 2.84$, $p = 0.004$), meaning that they were more interested in or confident in utilizing AI technologies. Age also had an effect on practice: professionals aged 30 - 39 ($\beta = 4.17$, $p < 0.001$) and 50 and beyond ($\beta = 10.01$, $p = 0.004$) had scores that were much higher than those aged 20 - 29. This could be because they had more responsibility or experience (Table 6). Job role turned out to be a powerful predictor. Senior laboratory technologists (β = 4.54, $p = 0.011$) and laboratory technologists (β = 3.35, $p = 0.010$) were both far more involved in AI-related work than laboratory technicians. Even while pathologists also had higher scores, the difference was not statistically significant. On the other hand, education (master's: β = 0.58, $p = 0.588$; PhD: β = -1.09, $p = 0.654$) and marital status (single: β = -0.14, $p = 0.966$; married: β = -3.54, $p = 0.239$) did not have a big effect on practice. Professionals with more than 10 years of experience had far lower practice ratings (β = -5.48, $p = 0.018$), which suggests that they were less engaged with AI, potentially because they did not get enough training or were unwilling to change. Age, gender, and job role were important factors in whether or not someone used AI. Education, marital status, and most levels of experience were not. These results show that we need to train junior and long-serving professionals in a way that includes everyone and is specific to their roles. This will help AI be used more widely and fairly in hematological diagnosis.

DISCUSSION

The goal of this study was to find out what medical laboratory professionals think and feel about using artificial intelligence (AI) in hematological diagnoses by looking at their knowledge, attitude, and practice (KAP) and finding important demographic and occupational variables. The main purpose was to find out how factors like gender, age, and work experience affect how laboratory workers use AI in labs. According to Obeagu [36], AI reduces observer variability, increases diagnostic consistency, and accelerates laboratory processing consistent with the results of this study, showing that knowledge, attitude, and practice were all strongly linked to each other, which was the initial research goal: to look into the relationship between KAP domains. The positive associations revealed earlier research that shows that gaining more information might lead to better attitudes and practices [20]. This shows how important it is to have structured AI education and hands-on experience with new technology to get people fully involved.

To meet the second research goal of finding demographic determinants of KAP, the results showed that gender and work role were important in all three domains. Males always scored higher than females on knowledge (β = 2.65, $p = 0.020$), attitude (β = 1.94, $p = 0.028$), and practice (β = 2.84, $p = 0.004$). Senior laboratory technologists also had higher scores in knowledge (β = 5.12, $p = 0.014$), attitude (β = 3.94, $p = 0.014$), and practice (β = 4.54, $p = 0.011$). This is probably because they had more duties, used AI tools more, and were in charge of others. Educational level was not a good predictor of any KAP dimension, which was not what it had been expected. This means that having a degree alone does not mean laboratory workers are good at AI. Instead, it seems that practical experience and job training had a bigger impact, especially on older participants and those in senior positions. Participants aged 30 - 39 (β = 4.17, $p < 0.001$) and 50 + (β = 10.01, $p = 0.004$) scored much higher in practice than those aged 20 - 29, which suggests that being more experienced makes people more interested in AI. This result is supported by an AI-powered system that was developed to detect blood cell anomalies and support telehealth hematology services, demonstrating high accuracy in morphological assessment and enabling early abnormality detection [36]. The system improves diagnostic access for underserved regions and reduces manual workload of individual experience in digital hematology workflows. Despite its strengths, broader validation across diverse populations to ensure generalizability and safe deployment in telemedicine settings were involved [37]. There have been reports of gender differences in the use and adoption of artificial intelligence (AI) in many fields. Men are more likely to be confident and familiar with technological fields, which can affect how they use AI products [38]. The result of this work showed that senior laboratory technologists did far better in all three KAP areas. More senior staff members frequently have more hands-on experience, make decisions, and have more responsibility, all of which helps people learn about and apply AI technology in labs. In addition to overseeing others, supervisors are often responsible for training, which encourages people to use technology more deeply. This finding agrees with the previous study performed by Bertl et al. [30]. Their study showed that individuals with higher levels of responsibility, especially those in supervisory or decision-making roles tended to engage more with AI, as they were accountable for ensuring its accuracy and effectiveness in critical healthcare decisions. Artificial intelligence is increasingly shaping hematopathology by optimizing the analysis of bone marrow biopsies, lymphoid tissues, and complex microscopic features. Furthermore, it improves diagnostic standardization and reduces time-intensive manual evaluation. Remaining challenges include limited annotated datasets, variability in staining, and the demand for explainable algorithms to support clinician trust and regulatory approval. Rather than replacing specialists, AI is expected to augment expertise and strengthen diagnostic confidence [39].

The fact that the educational level did not significantly predict any of the KAP aspects means that formal education alone is not enough to make sure that someone is good at using AI in real life. It seems that real-world involvement, on-the-job training, and practical learning have a bigger effect on how people think and act when it comes to AI in health laboratories as supported by a previous study [29].

The study emphasized that hands-on interaction and workplace adaptation play a greater role in successful AI use than formal educational background. They also noted that age and professional experience positively influenced users' familiarity and confidence with AI, reinforcing the idea that repeated, real-world exposure improves practical engagement. The result also suggests that older professionals may be more careful about using AI, but they may be better at using it because they are important for quality control and diagnostics. A recent study backs this up by noting that healthcare professionals with longer field experience and greater exposure to clinical environments were more adept at using explainable AI systems [27]. Their study suggested that institutional familiarity and accumulated practical knowledge played a key role in enhancing user competence and trust in AI tools.

This study differs from previous research by recognizing it is the first of its kind to examine KAP (Knowledge, Attitude, Practice) among medical laboratory personnel specifically in hematology laboratories. While Alyousef et al. [4] assessed general AI perceptions among clinical laboratory professionals did not analyze KAP domains nor conduct regression modeling. Similarly, Alanzi et al. [7] surveyed hematologists, not laboratory technologists, and focused on clinical decision-making, not hands-on diagnostic workflow. This is the first study to quantify KAP scores and identify predictors (gender, job role) using inferential statistics, it is also the first specifically for hematology diagnostic laboratory personnel.

The final goal of the research was to find institutional or systemic issues that might affect the use of AI. Even though the cross-sectional design made it hard to draw causal inferences, the patterns that were seen point to institutional exposure, leadership possibilities, and access to ongoing training as key factors. For instance, the fact that experienced professionals have better KAP ratings is similar to what was found in two previous studies, which both showed similar trends in laboratory staff's infection control and biosafety methods [40,41]. The gender discrepancy found in all KAP scores is important because it shows that training and policy changes need to be made to make sure that everyone has the same level of exposure and confidence.

The primary outcomes of the study are grouped into two directions, namely: demographic findings and professional predictors. These derive from the descriptive analysis and the evaluation of the association of the research variables in the inferential statistics. Typically, it was established that significant influence of knowledge, attitude, and practice (KAP) of medical laboratory personnel toward the use of AI in diagnostic settings. Job role emerged as a major determinant of AI knowledge, attitude, and practice, with senior laboratory technologists. This is a crucial result, which is acknowledged to be one of the primary outcomes. It also indicates that males demonstrate higher knowledge ($\beta = 2.65$, $p = 0.020$), more positive attitudes ($\beta = 1.94$, $p = 0.028$), and stronger AI-related practices ($\beta = 2.84$, $p = 0.004$). Similarly, this is supported by Cachero et al. [35], which directly shows significant gender-based differences in AI knowledge and perception, matching the findings.

The study also revealed strong interrelationships among the KAP components, this is also a crucial finding that can be described as the primary outcome, showing high positive correlations between knowledge and attitude ($\rho = 0.722$, $p < 0.001$), knowledge and practice ($\rho = 0.886$, $p < 0.001$), and attitude and practice ($\rho = 0.734$, $p < 0.001$), confirming that higher knowledge is associated with greater readiness to embrace AI. This is in the same direction with the work of Sula et al. [41] which confirms the structure and interdependency of KAP models, even though it applied to infections.

Another important aspect of the primary outcome lies with the median scores for knowledge, attitude, and practice (34, 35, and 35, respectively). This indicates strong AI readiness among respondents, with scores clustered toward the upper end of the scale. As a result "age" had selective influence on AI practice, particularly among the 30 - 39 and ≥ 50 age groups, while those with more than 10 years' experience showed significantly lower practice levels ($\beta = -5.48$, $p = 0.018$). It has been established that "education level", "marital status", and most "age" categories were not significant predictors. This result is supported by the research work of Alanzi et al. [7], which provides evidence that demographic factors such as age and experience influence AI acceptance differently.

The secondary outcomes offered supplementary contextual and descriptive insights regarding the study population and methodological observations that enhanced the original findings. The descriptive profile revealed that 113 participants completed the survey, predominantly characterized as youthful (87.6% aged 20 – 39), highly educated (65.5% holding bachelor's degrees, 26.5% master's degrees, and 8.0% PhDs), and exhibiting moderate gender diversity (31.9% women).

SUMMARY AND RECOMMENDATIONS

This study gives us useful information about what medical laboratory workers know, think, and do (KAP) when it comes to using Artificial Intelligence (AI) in hematological diagnosis. The results show that the KAP dimensions are very closely linked to each other. For example, having more knowledge and a positive attitude is linked to using AI technologies more effectively and with more confidence in practice. The analysis found that gender, age, and job role were all important factors in predicting KAP scores, with men and senior professionals consistently scoring higher in all areas. It is interesting to note that university degrees and work experience were not very good predictors. This suggests that hands-on experience and learning in the real world may be more important for developing AI skills than formal academic credentials. In addition, there is an urgent need for tailored, inclusive training programs that teach AI literacy at all levels of laboratory work. Extra care should be taken to help women professionals, junior staff, and long-time employees, who may have trouble getting involved or accessing resources. To make sure that AI is adopted in a fair and long-lasting way, institutions need to include AI skills in their policies, performance reviews, and continuous professional development plans. Healthcare organizations can build a skilled, AI-ready workforce that can use sophisticated technologies to improve diagnostic accuracy, operational efficiency, and patient outcomes by addressing differences in access, exposure, and confidence. At the end, it shows how important institutional support, inclusive policy design, and experiential learning are for the future of AI use in clinical laboratories. This study looks at all the KAP and demographic factors that affect AI adoption. It is also one of the few research projects that compare their results to real-world factors such as job role and work experience. Despite the success of the research approach, certain limitations should be mentioned. While the research utilized a cross-sectional design to examine issues related to AI, drawing subjective definitive conclusions about cause and effect might face some drawbacks associated to bias. Pérez-Guerrero et al. [42] support this view by highlighting that wherever simultaneous, cross-sectional study cannot establish causal relationships, it can lead to determine an association. This can further be justified by including assessment of data integrity measures like anonymity, pilot testing. Instrument validation has been employed to mitigate the effects of perceived based. Yet relying on self-reported data remains inclined to biases associated with social desirability or recall. However, the study's design, which was limited to a single site, implies that the conclusions can be cited and reproduced to other healthcare systems. This is because different health organizations use different lab approaches on AI. Based on this limitation, the study recommends that future research should incorporate wider approach to enhance generalizability, validate identified relationships, and provide a more comprehensive contextual understanding of AI adoption in diverse laboratory environments.

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Declaration of Generative AI Use:
The author declares that generative AI was used solely to enhance grammar, clarity, and language flow during manuscript preparation. All scientific content, study design, data analysis, interpretations, and conclusions are entirely the author's own and were not generated by AI.

Declaration of Interest:
The author has declared that no conflict of interest is associated with this publication.

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