Research Article

Conceptualization of the Use of Artificial Intelligence by Clinical or Research Laboratory Professionals: Challenges for Its Implementation in Mexico

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Abstract

Introduction: Artificial intelligence (AI) is revolutionizing the healthcare sector via advanced tools to improve diagnostic accuracy, operational efficiency, and decision-making. In clinical laboratories (CLs), the integration of AI automates the processing and analysis of large volumes of data, enables the early detection of diseases, and supports personalized medicine. Determining how personnel involved in the use of AI in CLs conceptualize AI can enable the identification of challenges and difficulties impeding its implementation.

Methods: An observational, prospective, cross-sectional, and comparative study was performed using an online survey for CL or research professionals in public or private CL throughout Mexico. The survey had 36 questions aimed at obtaining sociodemographic information and conceptualization of different aspects of AI, namely, familiarity, use, concerns, limitations, and useful applications.

Results: Overall, 125 men and 237 women (aged 19–81 years) participated in this study. The survey results showed that CL or research professionals were familiar with AI in general. They preferred to use AI to reduce pre-analytical errors (67%) and save time (65%). Lack of knowledge and training (74%) and fear of being replaced (66%) were identified as major AI-related concerns; the ethical aspects of AI were also a main concern. Only 4.7% of respondents had received formal AI training, but 84.8% were willing to take AI courses.

Conclusion: The findings highlight opportunities and priorities to promote AI-related public and educational policies, regulate AI adoption in CLs, develop optimal training strategies, as well as foster ethics, avoiding the exclusion of particular social groups.

Introduction

Quality management in clinical laboratories (CLs) must evolve to address not only process control but also the complexity of patients and their environments. Quality in CLs encompasses multiple aspects, such as total control, assurance, reengineering, innovation, and continuous improvement, all of which require a data-driven approach to ensure reliable results. It is critical that standardized laboratory test results are obtained accurately within defined limits, minimizing pre-analytical, analytical, and post-analytical errors and considering inter- and intra-assay variations, along with the heterogeneity of human factors that influence decision-making [1-3].

Since the 1950s, automation in clinical practice has transformed data management and administrative calculations. In the last 20 years, artificial intelligence (AI) has accelerated this evolution with advanced applications in automated image analysis, algorithms, expert systems for diagnosis, and mass processing of clinical data. AI currently enables the analysis of large volumes of data (big data), facilitating the development of predictive models and optimizing diagnostic quality in clinical practice. Its implementation has improved test accuracy, operational efficiency, and the ability to quickly predict errors or diseases [4-7].

Now the integration of AI in CLs is revolutionizing healthcare by enabling advanced analysis, diagnostic algorithms, personalized treatment, and process optimization. Globally, AI has demonstrated benefits in areas such as digital pathology, molecular test interpretation, and medical image analysis [7-9], however, in low- and middle-income countries, such as Mexico, its implementation faces significant challenges due to inequalities in access to technology, variability in CL infrastructure, and the need for specialized training. Although Mexico has witnessed isolated efforts to integrate these tools, a comprehensive assessment of their adoption, benefits, and specific obstacles nationally has not yet been conducted. To effectively integrate AI into their work, CL staff must conceptualize its application in existing processes, understand its benefits, and develop training strategies that ensure its ethical and efficient use [9-13].

As reported in various studies, AI-based technologies have significantly improved diagnostic accuracy, operational efficiency, and the personalization of healthcare. In particular, advanced machine learning (ML) algorithms have achieved performance comparable and even superior to that of human experts in detecting diseases such as skin cancer [14]. Furthermore, these tools are used to interpret molecular tests, identify abnormalities in clinical analyses, and predict complications in patients with chronic diseases. However, a range of studies have highlighted the need for further research and strict regulations to ensure their safety and utility as support systems for healthcare professionals, contributing to the improvement of clinical outcomes, reduction of waiting times, lowering of healthcare costs, and reduction of workload [14-19].

In response to the need to improve care for chronic diseases worldwide, AI is increasingly contributing to control of these and other diseases. A recent bibliometric analysis on the use of AI in chronic diseases examined 341 publications from 775 institutions in 55 countries, published in 175 journals between 2013 and 2024, indicating that 95% of these studies focused on four key areas: diagnosis, healthcare, telemedicine, and health technology [18]. Elsewhere, analysis of current trends highlighted the rise of mobile health and ML as fundamental pillars in the progress of AI clinically [18-21].

The incorporation of artificial AI into CL processes almost imperceptibly induces behavioral changes, which are closely linked to the conceptualization of these technologies and the perceived risks and benefits. In this context, the Prochaska and DiClemente model posits that behavioral change is not a linear process but rather progresses through distinct stages: precontemplation, contemplation, preparation, action, maintenance, and termination. Each stage represents a different level of readiness for change, and individuals may transition between stages at any time. This model also underscores the importance of motivation and self-efficacy in facilitating behavioral change [22].

This study was conducted to assess the conceptualization of AI by CLs and research professionals, identifying the challenges facing its implementation and the opportunities to optimize its use in Mexico. An analysis based on the findings of a nationwide survey explored the main applications of AI in CLs, the expected benefits, the barriers to its adoption, and the perceptions of AI among the specialized personnel at CLs. The findings of this work should provide a foundation for the development of public policies that regulate the implementation of AI, the establishment of training strategies for those tasked with using AI tools in CLs, and measures that encourage the responsible adoption of AI in order to improve the quality and accessibility of diagnostic services in Mexico.

Materials and Methods

This research was carried out via a survey aimed at CLs or research professionals working in any field (administrative or analytical processes), male or female, of any age, and with at least a technical degree, from public institutions or private laboratories throughout Mexico.

The survey was designed based on a previously validated instrument [23] to which questions were added to analyze additional variables considered important in the context of the present study. The instrument consisted of a total of 36 questions. The first section of the survey prior to the questions, included a description of the objective of the research and requested informed consent, along with assurances that participation was voluntary and anonymous. The first eight questions were related to sociodemographic variables (e.g., age, sex, years of experience in their current position, educational level) and where in the laboratory/office the respondents performed their professional activities; 25 questions were directed to the conceptualization of different aspects of AI such as familiarity, daily use of AI-based applications, AI knowledge, processes for which AI could potentially be useful, and fears and challenges regarding its implementation. Of these latter 25 questions, 18 were multiple-choice questions for which one or more answers were allowed; for the other seven questions, a 5-point Likert scale ranging from 1 ("highly disagree") to 5 ("highly agree") were made. Finally, three optional questions were included to collect additional comments on the content of the instrument.

To ensure linguistic accuracy and cultural relevance, four experts validated the translation of the survey instrument into Spanish, considering the cultural context of the Mexican study group. They assessed the appropriateness of the questions, the accuracy of additional items, and the order of presentation to ensure alignment with the research objectives. Furthermore, they evaluated the response options to maximize the likelihood of obtaining truthful responses. A pre-test (pilot test) was conducted with 10 workers from various laboratory departments to identify and mitigate potential sources of random error.

The surveys were distributed from November 2024 to January 2025 through WhatsApp or email, and the corresponding Google forms link to access the survey to representatives of Colleges of Professionals in the CL field, both public and private, and to researchers in research laboratories at universities and research centers in all eight geographical regions into which Mexico is divided. The survey was accompanied by a 35 s video featuring an AI-created character, who welcomed the participants and explained the scope and objectives of the research, in addition to thanking those responding to the survey.

Statistical analysis

Statistical analysis was performed using NCSS software version 2020, with a methodological approach that combined descriptive statistics and nonparametric inference tests. Categorical data were summarized using absolute frequencies and percentages, while quantitative variables were analyzed with measures of central tendency and dispersion. For comparisons of qualitative variables between groups, the chi-square test (χ^2) was applied as a non-parametric method, selected for its suitability to the type of data and the assumptions of the study. The interpretation of the results was based on the p-value obtained, with the threshold for statistical significance set at $\alpha<0.05$. This criterion allowed the determination of statistically relevant associations between the analyzed variables. The process included initial characterization of the sample using distribution tables; bivariate analysis with contingency tables; the application of corrections for tables with low expected frequencies; and confirmation of the validity of the assumptions on which the choice of each statistical test was based. This methodological approach guaranteed rigorous treatment of the data, which is particularly important in studies with non-normally distributed data or small samples.

Results

The survey was initially distributed to 491 contacts via email and WhatsApp, with a request to further disseminate it using the snowball method. However, not all emails and messages were confirmed as received, making it impossible to determine the exact number of surveys distributed and, consequently, the response rate.

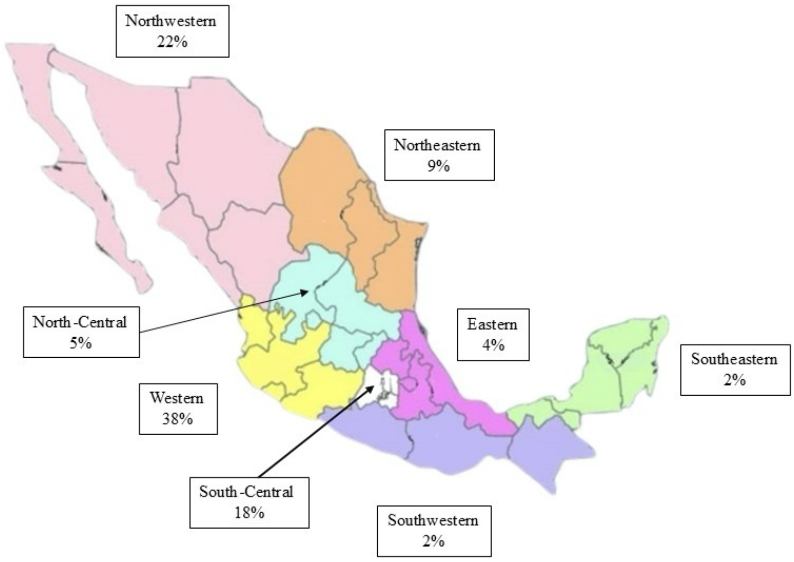
A total of 364 responses to the survey on AI in CLs were received from November 15, 2024, to January 15, 2025. Two responses were excluded from the analysis: one because the individual was from another country (Portugal) and the other due to inconsistencies found in the responses. As such, the analysis was carried out on 362 surveys, corresponding to 125 men and 237 women between the ages of 19 and 81 (mean±SD: 43±13.6). The subjects varied in their educational level, years of experience in their current job, and whether their professional activities were performed in the CLs or involved administrative work. They worked in either public or private laboratories, which were classified by size (i.e., number of employees) and geographical area (Table 1; Figure 1). Overall, 53% of the participants reported having 1 to 10 years of experience (47 of them with <5 years of work experience) and 47% had ≥11 years in their current position. Of the 76 managers, 68 also performed laboratory tests, while 8 only performed managerial activities. Meanwhile, 29 participants only worked in administrative areas, and the rest (n=257) performed both laboratory and administrative activities, particularly in micro- and small laboratories.

Table 1: Participant and laboratory characteristics.

PARTICIPANTS	**n**	**%**
Sex		
Female	237	65.4
Male	125	34.5
Age (years)		
18–26	45	12.4
27–59	266	73.4
>60	51	14
Education:		
Technical baccalaureate	42	11.6
Bachelor's degree	175	48.3
Postgraduate training in a CL specialism	43	11.8
Postgraduate degree	102	28.1
Professional activities:		
Managers	76	21.0
Administrative	204	56.3
***Laboratory:**		
Hematology	178	49.1
Immunology	157	43.3
Bacteriology and microbiology	131	36.1
Clinical pathology	94	25.9
Molecular biology	87	24
Years of experience:		
1–10	192	53.0
11–20	82	22.6
21–30	47	12.9
>30	41	11.3
LABORATORIES		
Sector:		
Public	158	43.6
Private	204	56.3
Size (number of employees):		
Micro- (<10)	116	32.0
Small (10–50)	155	42.8
Medium (51–100)	54	14.9
Large (>100)	37	10.2
Type:		
Clinical laboratory	342	94.4
Research laboratory	20	5.5

*Only the five most common fields are shown.

Figure 1: Geographical regions of Mexico and their constituent states.



1. Northwestern: Baja California, Baja California Sur, Chihuahua, Sonora, Sinaloa, and Durango; 2. Northeastern: Coahuila, Nuevo Leon, and Tamaulipas; 3. Western: Colima, Jalisco, Michoacan, and Nayarit; 4. Eastern: Hidalgo, Puebla, Tlaxcala, and Veracruz; 5. North-Central: Aguascalientes, Guanajuato, San Luis Potosi, Zacatecas, and Queretaro; 6. South-Central: State of Mexico, Morelos, and Mexico City; 7. Southwestern: Chiapas, Guerrero, and Oaxaca; and 8. Southeastern: Campeche, Yucatan, Quintana Roo, and Tabasco,

Familiarity

The subjects were asked about their degree of familiarity with the use of AI in general and with AI specific to CLs. Only two considered themselves experts (0.5%). Table 2 shows the results of familiarity for both AI in general and AI specific to CLs. The analysis shows that the participants were significantly less familiar with specific AI applications in CLs. In addition, participants with postgraduate training in a CL specialism or postgraduate degrees were more familiar than those with bachelor's or technical baccalaureate degrees (p=0.0007). Meanwhile, 140 of the participants (38.6%) asserted that AI was not used in their laboratory, 108 (29.8%) reported that it was, and 114 (31.4%) were not sure.

Table 2: Degree of familiarity with AI in general and specific to CLs.

Degree of familiarity	AI in general n (%)	AI specific to CLs n (%)	p
Expert	2 (0.5)	1 (0.2)	p=0.564
Very familiar	45 (12.4)	21 (5.8)	p=0.004
Something familiar	197 (54.4)	128 (35.3)	p=0.001
Little or not at all familiar	118 (32.6)	213 (58.8)	p=0.00001
Total	362 (100)	362 (100)	

Daily use of AI tools

First, the respondents were asked whether they used AI applications on a daily basis, with three possible and exclusive answers ("Yes," "No," and "I'm not sure"). They were provided with a list of common applications from which they could choose all those that they used on a daily basis. MetaAI (WhatsApp) was the most widely used (65.7%), followed by ChatGPT (45.5%) and Google Lens (33.7%) (Table 3).

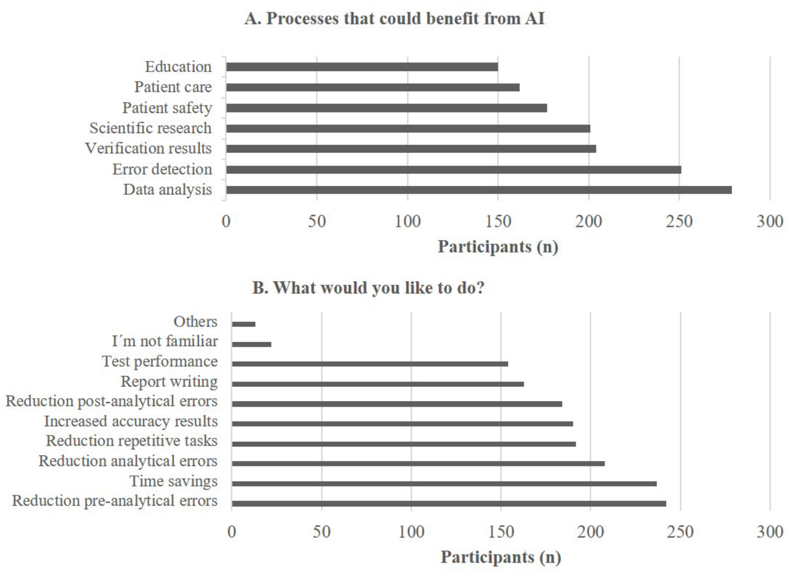
Table 3: Daily use of AI tools.

Application	n	%
MetaAI (WhatsApp)	238	65.7
ChatGPT	165	45.5
Google Lens	122	33.7
Snapchat	72	19.8
Google Bard	53	14.6
Grammarly	36	9.9
Bing	23	6.3
Copy.ai	12	3.3
Perplexity	10	2.7
Scite	7	1.9
Quillbot	3	0.8
Tome	1	0.2
DeepSeek	1	0.2
Others	43	12.5
I don't know or use any	49	13.5

Benefits of AI in the laboratory

Overall, 78% (n=283) of the subjects were sure that AI was used for laboratory processes, while 19% (n=70) reported that this may be the case and 2% (n=9) were not sure. According to the participants, the three types of tasks for which AI could be most beneficial were data analysis, error detection, and verification and presentation of results. Meanwhile, the three purposes for which the professionals would most like to use AI in CLs were reduce errors in pre-analytical stage, to save time, and to reduce errors in the preanalytical and analytical stage (Figure 2).

Figure 2: Tasks for which AI could be most beneficial and what would you like to do.



Processes that can be automated

More than 50% of the participants asserted that AI tools could enable the automation of administrative processes, quality control, repetitive tasks, and numerical data management in CLs (Table 4). Participants with a higher academic degree (Postgraduate training in a CL specialism or postgraduate degree) showed a greater tendency to assert that AI could be used to predict values based on other results ($p<0.00001$). Overall, 75.4% (n=273) of respondents supported the idea of implementing AI tools in the laboratory, and 52.2% (n=189) thought that such implementation should be carried out in the near future. Moreover, those with higher academic degrees also exhibited a greater tendency to think that AI could increase the precision and reliability of the results in CLs ($p=0.0374$ and $p=0.0005$, respectively).

Table 4: Processes that could benefit from AI in CLs.

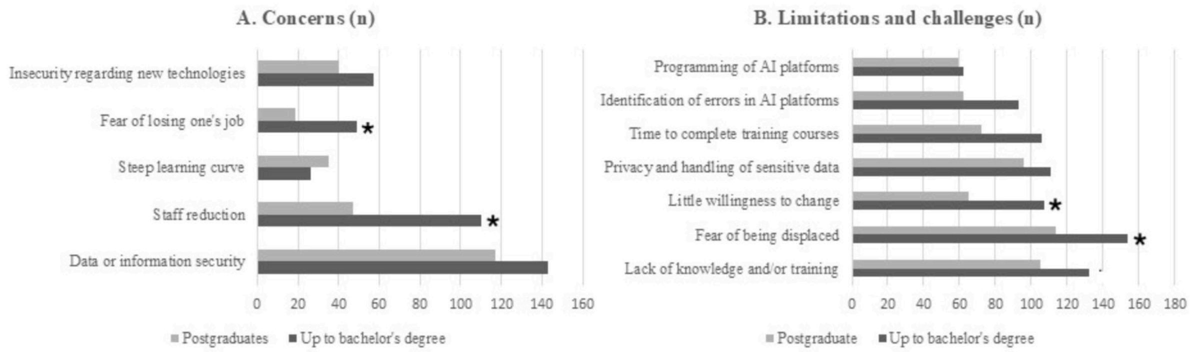
Processes	n	%
Administrative processes	282	77.9
Quality control and/or error identification	251	69.3
Repetitive tasks	210	58
Handling numerical data	200	55.2
Workflow	172	47.5
Set custom reference ranges	163	45
Efficiency of diagnostic processes	157	43.3
Accuracy of diagnostic processes	155	42.8
Suggestions for additional testing	147	40.6
Predicting values based on other results	133	36.7
Interpretation of results	132	36.4
Interaction with patients	132	36.4

Significantly, 52% of participants considered that AI will replace humans in performing certain tests in CLs, with this proportion not differing depending on the type or size of the laboratory. However, this rate did differ depending on the academic level of the participants, with those with higher educational levels being more likely to hold this opinion ($p=0.0005$).

Concerns, limitations, and challenges

Overall, 73.5% of the participants were concerned about their own lack of knowledge or training in the use of AI, 65.7% were afraid of losing their jobs to AI, and 58.2% were concerned about the lack of willingness of CL management to introduce AI tools into the workplace. Regarding ethical aspects, 71.8% were concerned about the security of the data fed into AI tools, and 50% were concerned about privacy and the handling of sensitive data. Three participants expressed concern about who would be held responsible for AI errors. Figure 3 shows the number of responses for each concern or limitation and challenges, and distinguishes the differences according to academic degree.

Figure 3: Concerns, Limitations and changes about AI.

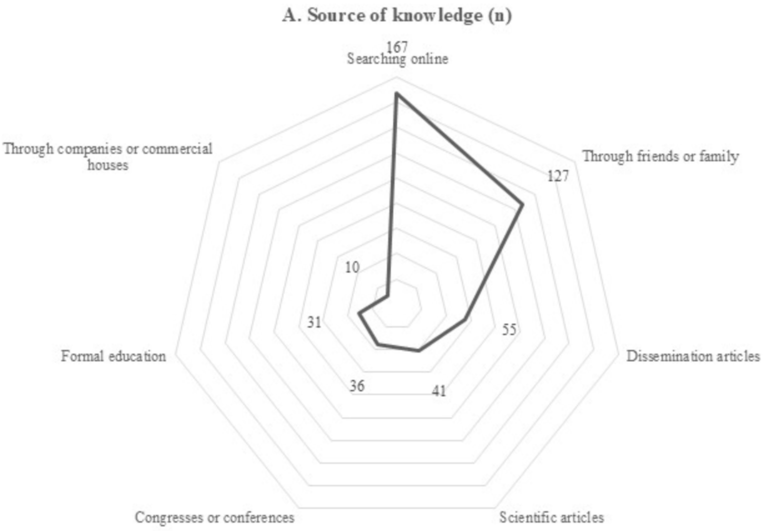


*p<0.05

Formal AI-related education and sources of knowledge about AI

Only 17 of the participants (4.7%) had received formal training in AI. Figure 4 shows data on how the participants learned about AI. Nonetheless, 84.8% reported that they were willing to be formally trained in AI and were not concerned about the steep learning curve.

Figure 4: Sources of AI knowledge among CL professionals.



Discussion

To develop public policies that effectively regulate the implementation of AI, and to design optimal training strategies and implement measures that promote its ethical and responsible adoption, there is a need to understand how CL professionals conceptualize or perceive AI. This would in turn improve the quality and accessibility of diagnostic services and benefit patients and the medical community.

AI applications, particularly those based on ML and deep learning (DL), play a crucial role in the pre-analytical, analytical, and post-analytical phases of the testing process in clinical laboratories. Significant advancements have been documented in various fields, including hematology, cytology, histopathology, biochemistry, immunology, microbiology, and urinary sediment analysis. AI applications have also demonstrated success in diagnosing malignant diseases and enabling longitudinal monitoring of biomarkers, allowing for the prediction of patient treatment outcomes [24–29]. Similarly, the utility of convolutional neural networks (CNNs), which utilize three-dimensional data, has been highlighted in the recognition of peripheral blood cell images [30].

A few recent studies have specifically attempted to analyze how CL professionals conceptualize AI, with results from Pakistan, Europe, and the USA [23, 31-33] and how health professionals and hematology students understand AI [34]. The shared objectives of these studies included exploring and analyzing perceptions of AI, conceptualization and/or attitudes toward it, degree of familiarity with AI, formal education in AI-focused courses, and willingness to adopt AI technologies in decision-making processes in diagnosis and treatment, as well as identifying opportunities, concerns, and challenges facing the implementation of AI. With the exception of the work by Jafri et al. [33] in which structured interviews with 13 participants were performed, other studies involved online surveys with between 10 and 36 questions, with our study considering the highest number of aspects.

To the best of our knowledge, this is the first study of CL professionals from public or private institutions on their conceptualization of AI in laboratories in Latin America. It was conducted without external funding and differs from other studies in that it includes professionals at research laboratories in addition to CL staff. Our study also distinguished between those working at micro-, small, medium, and large laboratories, defined according to the number of employees.

This study was based on a previously validated instrument to which questions were added to obtain a broader overview of attitudes towards AI and the status of its implementation in CLs, including sociocultural characteristics and the social context of the Mexican population. This constitutes a major strength of our study, as well as having included different categories of operational and administrative CL-related work. The survey was self-administered, anonymous, and electronically distributed, minimizing interviewer bias (e.g., tone of voice and gestures) and encouraging honest responses, particularly because not address sensitive or personal topics. Nevertheless, a limitation was the lack of control over the response rate, which may have impacted the findings by introducing response bias, reducing statistical power, and limiting the generalizability of the results to a broader population. Despite these limitations, we believe that the variability in profiles among CL workers across the eight geographic regions of Mexico—both in public and private sectors—is not significant enough to compromise the objectives of this exploratory study. We ensured that responses were obtained from all geographic regions (Figure 1).

The limited number of participants can be explained by the large number of questions in the survey, the target group's resistance to evaluation, or concerns among the participants regarding cybersecurity, since most had to use personal electronic devices to complete the survey. Nonetheless, all geographical regions of Mexico were represented in the sample. For comparison, in other similar studies, the analysis was carried out on 13 (Pakistan), 195 (in 34 European countries), 342 (Pakistan), and 1,721 participants (USA) [23, 31-33]. Official Mexican data indicate that women make up more than 55% of the labor force in CLs; they most commonly have a background in chemistry, and 11% of those employed in this sector have a master's or doctorate degree [35]. This contrasts with 28% of participants who had a postgraduate degree in our sample. Furthermore, the majority of respondents worked in private laboratories (56%), where AI might well be more widely used.

The characteristic of being "Somewhat familiar" with AI dominated in all of the studies performed (54% to 64%), including ours. However, this contrasts with the low familiarity with AI specific to CLs, the perceived need for CL staff to receive AI-related courses and training, and concerns about regulation, transparency, and ethics.

When the respondents were asked if they used AI applications on a daily basis and, if so, which ones, the answers were inconsistent. Specifically, those who answered "No" selected several applications, which shows an imprecise understanding of which tools are actually AI-based.

Regarding the first four benefits that professionals would like to pursue if they were to apply AI (save time, perform tests, reduce errors, and reduce repetitive tasks), the comparison with other studies showed that these potential benefits were mentioned at higher rates in Mexico than elsewhere [23,31].

Studies on the perceptions of AI have reported that such perceptions are influenced by cultural, educational, structural, and economic factors [22, 23, 31-33]. In this study, more than half (58.1%) of the participants expressed their own unwillingness to change regarding the adoption of AI, an attitude that should be modified through specific training to take advantage of the precontemplation and contemplation stages they find themselves; and that, according to the Prochaska and DiClemente model, are phases that a person needs to overcome in a change process [22].

The results of this study show that in Mexico there is a need to promote the effective adoption of AI in CLs and to implement education and training programs on AI at certified centers that guarantee ethical use, transparency, and security in the use of AI algorithms. It is also necessary to design public policies and regulations that promote the effective integration of AI tools in CLs, without excluding certain social groups, in adherence with best practices and the common good [36-38]. There is a need for Mexican CLs to obtain specific national and international accreditations to operate AI technologies, including those with or without ML. In CLs, decisions will have to be made about the type of technology and specific applications to use according to the identified needs [20,39].

Opportunities in Education

According to the responses provided by our sample, and as reported by Cadamuro et al. [32] and Jafri et al. [33], there is a need to implement regulation and to standardize ethics and norms for AI via training courses in Mexico, since only 4.7% of our respondents had received a formal education in AI. AI is not currently included in the syllabuses of healthcare-related undergraduate courses in Mexico; as such, formal education on this topic should be initiated, accompanied by modification of the syllabuses of healthcare-related courses and incorporation of continuous professional development courses for professionals aligned with international standards such as ISO 15189, the official standard for medical laboratories, setting out the requirements for quality and competence [40]. In addition, certification that ensures that CL staff fully understand the functioning of AI tools and correctly interpret the results should be actively pursued. The gap between end users and developers identified in medicine could be narrowed via the contributions and participation of CL professionals and other healthcare professionals, with experience and formal education in AI for the implementation and adaptation of these technologies in specific clinical contexts [41].

Ethical challenges

The rapid advance in the use of AI in the healthcare sector is accompanied by significant ethical challenges, including concerns about reliability, transparency, bias, and data privacy, as well as the risk of AI replacing CL professionals, as identified in this study. It has been proposed that assuaging these concerns and mitigating these risks requires a proactive approach, including determining the minimum data required for a specific purpose and limiting collection to what is strictly necessary, obtaining informed consent from patients for AI tools to use their data through clear communication, anonymizing personal data, incorporating privacy considerations into AI design ("privacy by design"), ensuring transparency in AI decision-making, regularly monitoring AI-related practices, and evaluating data models for emerging risks. From an ethical perspective, it is particularly important to ensure that rather than replacing humans, AI should complement their expertise and enhance their work in professional practice [42].

In the field of AI, the term "integrated ethics" refers to the ongoing practice of prioritizing ethics in the entire AI development process in a collaborative and interdisciplinary manner. This involves the systematic promotion of explicit and robust normative analysis and the use of ethical reasoning to justify or question a particular position or course of action [43]. Among the concerns associated with the use of AI in the healthcare field are regulations, meta-ethics, epistemology, medical practice, medico-legal concerns, the need to uphold patients' and physicians' rights, and the potential risks posed by predictive analytics [44], which must be explicitly considered in initiatives to legislate on this topic.

Conclusions and perspectives

Based on the findings of the present study and given the rapid development of AI in this sector, the appropriate incorporation and utilization of AI must involve the implementation of ex post surveillance systems to detect problems or errors in its daily use. There is also a need for the reporting of adverse events related to AI tools, protocols that identify and correct biases in the data on which algorithms are trained, and validation that AI tools are effective for diverse populations and do not generate healthcare inequalities in diagnosis or treatment.

It is also necessary to propose and ratify complementary laws and regulations that establish an appropriate framework to guide the development, implementation, and use of AI in CLs; to promote collaboration between academic institutions and industry; to develop regulations that can adapt to technological advances; and to participate in global initiatives to standardize the regulation of AI in the healthcare sector and promote the exchange of best practices and knowledge internationally. Moreover, there is a need to create procedures for clearly establishing where responsibility lies (e.g., with the AI tool developer, with the laboratory, or with the professionals who operate the system) in cases of diagnostic errors or problems arising from the use of AI in CLs.

The findings of this study can serve as a basis for defining opportunities and priority areas to promote public policies that encourage the adoption of AI in the CL sector, along with the implementation of appropriate training strategies. This work can also help foster the more extensive, regulated, ethical, and effective implementation of these technologies, with the aim of improving the quality and accessibility of services and avoiding the exclusion of particular social groups from accessing the most accurate possible clinical diagnosis.

This initial exploration of the conceptualization of AI among CL professionals in Mexico highlights an opportunity for further research. Future studies should focus on validating AI tools within specific CL contexts and employing different study designs (e.g., longitudinal or qualitative approaches) to assess the adoption and acceptance of AI over time. Additionally, future research could analyze the experiences of professionals in specific laboratory areas and facilitate cross-national comparisons to better understand the broader impact of AI in CL settings.

This should help to improve the diagnosis and prognosis of diseases and promote technological development for the benefit of patients while considering the needs and wishes of clinical doctors who order laboratory analyses, generating continuous communication among doctors, patients, and laboratory staff.

Finally, the results of this study highlight the need to implement AI more intensively in CLs in Mexico and an interest in resolving the main limitations and challenges obstructing its implementation. We conclude by stating that rather than fearing being replaced, those who are trained in the use of regulated, standardized AI, along with robust and transparent ethics, should have better opportunities for ongoing professional development in this field.

Declaration of Conflict of interests

The authors declare that they have no material or financial conflicts of interest relevant to the research described in this article.

Ethical Approval

The study was conducted with the ethical principles for medical research involving human subjects, in accordance with the Declaration of Helsinki (Oct., 2024 revision) and approved by the Ethics Committee of the National Institute of Learning, Skills, and Research in Sciences, SC (Registration number CIE-INHAIC-2024-013).

CRediT author statement

The contributing roles of all authors in the research, review and editing of this manuscript are named:

JMSG: Conceptualization, Methodology, Validation, Investigation, Data Curation, Visualization, Supervision, Project administration, Writing - Original Draft, Writing - Review and Editing.

MCMM: Conceptualization, Methodology, Validation, Investigation, Data Curation, Visualization, Supervision, Writing - Original Draft, Writing - Review and Editing.

AERC: Validation, Formal analysis, Data Curation, Visualization, Writing - Review and Editing.

EJRB: Validation, Formal analysis, Data Curation, Visualization, Writing - Review and Editing.

RISA: Validation, Writing - Review and Editing.

JHPG: Writing - Review and Editing.

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