

Revolutionizing Medical Laboratory Diagnostics through Artificial Intelligence and Multi-Criteria Decision-Making: An Application of TOPSIS and VIKOR Methods

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Abstract

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Artificial intelligence (AI) is rapidly changing clinical laboratories, but it has limited the ability to translate research findings into practice. To guide future development and adoption of AI, it is important to understand the current state of use of such applications as well as the benefits they provide; also to recognize persistent implementation barriers. The aim of this systematic review is to evaluate the current applications of artificial intelligence in laboratory medicine, assess the

measurable improvements in diagnostic accuracy, operational efficiency, and error reduction, identify technical, regulatory, ethical, or workforce-related challenges, as well as provide evidence-based recommendations for successfully implementing AI in clinical settings. This paper focuses on the applications of AI in clinical laboratory settings and examined peer-reviewed literature published between 2014 and 2026. Machine learning, deep learning and natural language processing along with computer vision applications across chemistry, hematology, microbiology, genomics and point-of-care testing domains were also reviewed. As a result, the study shows that AI technologies can now deliver diagnostic accuracy > 90% in many applications; reduce unnecessary testing by up to 50%; cut turnaround times from 23-60%; increase result reliability by 25%; and reduce preanalytical errors by 30%. In laboratory medicine, artificial intelligence has the potential to revolutionize diagnostic accuracy and operation, while also improving patient outcomes. Achieving this potential requires a coordinated approach across research, regulatory and institutional levels, as well as across educational institutions. The priority areas are the establishment of strong validation frameworks, transparent regulatory pathways, investment in interoperable infrastructure, comprehensive training programs for laboratory professionals, algorithmic fairness, and sustainable AI practices. Laboratory medicine is poised to become a future where human expertise and artificial intelligence work together to provide accurate, personalized, and globally accessible diagnostics.

Keywords: Artificial Intelligence, Laboratory Medicine, Machine Learning, Diagnostic Accuracy, Clinical Laboratory, Healthcare Implementation

1. Introduction

The way labs operate is being transformed by artificial intelligence.? This is making the task of identifying patient issues more effective and precise. This also facilitates the

provision of care to patients. We examined the current implementation of artificial intelligence in laboratories.' Our ability to discern between successful and unsuccessful outcomes was evident. The reason for the lack of universal intelligence utilization was uncovered. We also reflected on the potential outcomes of intelligence in labs. Our investigations demonstrated that artificial intelligence is highly proficient at identifying issues with patients.'". There may be a percentage exceeding 90%. Artificial intelligence has the potential to decrease the number of tests by as much as 50 percent. It has the potential to quicken the testing process by 23 to 60 percent. By doing so, the results become 25 percent more dependable. Artificial intelligence is adept at minimizing mistakes before the actual testing process. By examining the specimens' quality and identifying clots, it can accomplish this. This can result in a 30 percent reduction in errors. Still, there are some significant issues to tackle. The effectiveness of artificial intelligence in certain situations is dependent on its proper functioning. We must ensure that all the data is in the format. We must establish the rules and regulations.' Our focus is on educating individuals in the labs about artificial intelligence. Some inaccuracies in the research conducted thus far are highlighted by this review. It offers suggestions for improving the performance of artificial intelligence in labs. The work involved formulating guidelines, conducting research, and educating individuals about artificial intelligence. This is demonstrated in the literature on artificial Intelligence (Aboulsoud et al. n.d.), (Alowais et al. 2023), (Khokhar et al. n.d),(Reiners et al. 2021).

Over the past ten years, clinical laboratories have undergone significant changes in their operations. Samples were taken, tests conducted, and outcomes distributed. Patients are now a part of their care. The realization that laboratory test results are the foundation for nearly 70 percent of all decisions resulted in this shift. The significance of laboratory medicine in healthcare today is highlighted by (Padoan and Plebani 2022). This statement. The amount of data is now handled by clinical laboratories. Furthermore, this data is extremely intricate. That presents both an opportunity and a significant challenge. A genomic report may contain tens of thousands of pieces of information that require comprehension. If someone tried to do this by hand, it would take weeks. This is why clinical laboratories really need help from computers. Artificial intelligence is an important tool for clinical laboratories. It helps them understand laboratory data quickly and accurately, as noted by (Davenport and Kalakota 2019) and (Padoan and Plebani 2022). Clinical laboratories and artificial intelligence are becoming more and more connected. This is changing the way laboratory medicine works (Topol 2026).

AI Approaches in Laboratory Medicine

Artificial intelligence is about computer systems that can do tasks that usually need intelligence. In laboratory medicine this includes approaches. These approaches are machine learning algorithms. Machine learning algorithms learn from data to make predictions (Alowais et al. 2023). There are also deep learning networks. Learning neural networks are good at understanding complex data patterns (Çubukçu et al. 2025) They are especially useful for looking at information. Natural language processing systems are another approach. These systems extract information from text. This includes pathology reports. Computer vision algorithms analyze data. They look at slides, culture plates, and biological specimens. A review by (Aboulsoud et al. n.d.) and colleagues in 2025 looked at 68 studies. The review found that machine learning, deep learning, computer vision, and natural language processing are commonly used in laboratory medicine. Artificial intelligence is good at diagnosis. It helps improve care. It reduces errors. It makes result quality. This review has goals. It wants to see how artificial intelligence is used in laboratory workflows. It wants to measure how artificial intelligence improves accuracy. It also wants to see how artificial intelligence improves efficiency and reduces costs. According to the review (Pillay, Khan, and Yenice 2025). "Technical challenges in compliance with EU regulations and other relevant regulatory bodies will be evaluated," as will workforce challenges. It'll also look at practices. It'll explore technologies. The utilization of these technologies may revolutionize the way laboratory medicine is done. The use of artificial intelligence will contribute to this change. Machine learning and deep learning are crucial areas of interest. The primary focus will be on computer vision and natural language processing (Xie, Zhang, and Wilson 2024).

Machine Learning Applications

Machine learning is an important technology for artificial intelligence in laboratory medicine. This technology employs algorithms like Random Forest and XGBoost to make predictions. Training the algorithms involves analyzing already labeled data and making predictions about new data. Their expertise lies in identifying diseases and forecasting their consequences (Altememi et al. 2026a), (Cabitza, Campagner, and Tontini n.d.). Machine learning is capable of identifying patterns in data without any assistance. This is called learning. By grouping cases and observing unusual outcomes, it can uncover inconsistencies or mistakes (Bietenbeck and Streichert 2021). Image analysis in laboratory environments is a particularly effective method for machine learning, such as convolutional neural networks. Parasites can be detected in stool samples by them. Define different types of blood cells. These networks are comparable to pathologists in

their proficiency in these tasks. The ability to analyze data that changes over time is a key feature of machine learning, unlike other neural networks. They are capable of observing patterns in laboratory and time-series data. Extracting information from text is another area where machine learning can be applied (Goodswen et al. 2021). This is called "natural language processing." It can automatically extract findings from pathology reports (Bhushan, Pandit, and Garg 2023). Classify microbiology results.(Mathison n.d.) It has the ability to mine research data and create Chabot interfaces for educational purposes. Machine learning and artificial intelligence are advantageous in the field of laboratory medicine. Machine learning and artificial intelligence are utilized to aid in the classification and prediction of disease outcomes (Paranjape et al. 2021).

Environmental Sustainability

Environmental sustainability is becoming a significant objective of artificial intelligence utilization. The investigation by (Liu et al. 2023). Compared nine algorithms (Liu et al. 2023). It was determined that five-layer neural networks use 16-24 percent less electricity than XGBoost. During that time, it performs equally well in classification tasks. The importance of selecting an algorithm that balances performance with environmental impact is highlighted. The investigation analyzed the operation of various algorithms for mass spectrometry and urinalysis. For spectrometry, Random Forest determined an AUROC value of 84.7 percent and for urinalysis it was 91.1 percent. Between 10.28 and 10.76 watts were utilized by it. The percentages for XGBoost were 83.9 and 91.4 respectively. Between 9.42 and 10.03 watts were utilized as power usage. The percentages for logistic regression were 82.0 and 87.8 respectively.? It utilized 9.70 to 9.98 watts.'In contrast, a five-layer neural network got 83.2 percent and 87.0 percent. It took 125.0 milliseconds to make a prediction. It used 13.08 watts of power. This shows that simpler algorithms can work as well. They use less energy and work faster. These findings are especially important in places where resources are limited. Both computer resources and energy costs are considerations there (Liu et al. 2023). They support the development of Green AI frameworks. These frameworks want people to measure and report how energy AI research and deployment are used. The goal is to make AI more environmentally friendly. This can help reduce the impact of AI. It can also make AI more accessible to people who need it.

Preanalytical Errors

The laboratory error happens a lot in the analytical phase. This phase is where 60 to 70 percent of all laboratory errors occur. So it is an important area where artificial intelligence can make a big difference. There are applications that show artificial

intelligence can make a significant impact (Lippi 2025), (Trory et al. 2023). For example, artificial intelligence can check the quality of specimens. A deep learning model was trained on 16,427 photographs of blood tubes. This model can accurately predict the quality of the specimens. It can automatically reject the specimens that're not suitable for analysis before it even begins. Artificial intelligence can also identify specimens that have clots. It does this by looking at pictures of the tubes. This prevents the laboratory from getting results from specimens that are not good. The artificial intelligence algorithms can also detect when the wrong sample is matched with the patient. It can do this with 85.5 to 93.1 percent accuracy (Zhou et al. 2023). This greatly reduces the risk of making errors. The analytical phase is another area where artificial intelligence is making a difference. Artificial intelligence applications are reducing errors by 30 percent. They are also making laboratory results more reliable by 25 percent. Deep learning algorithms is performing as well as tested by pathologists in some areas (Artificial Intelligence in Language Education 2025). There was a study by (Zhu n.d.) and colleagues in 2025. An intelligence-based verification system was also designed by them. The time taken to obtain results was 23.6 percent shortened by this system. The way things are done is similar to this. It is clear that artificial intelligence is significantly enhancing lab productivity. More accurately and faster results are being obtained in the laboratory with the help of artificial intelligence. In order to reduce errors, the laboratory is employing intelligence.? It is important to use artificial intelligence in the laboratory.

Quality Control and Analytical Applications

Statistical quality control applications using machine learning have shown capabilities. They reduced flagged outliers from 600 to 20 in validation studies. These algorithms are good at finding patterns across parameters. They flag results that need review with high sensitivity (Zhu n.d.). These abilities are supplemented by natural language processing tools. They create comments that aid in making decisions. The CURATE. The AI platform serves as an illustration of personalized medicine. Clinicians are able to estimate the chemotherapy dose for each patient by considering their treatment response patterns and profile (Pillay, Khan, and Yenice 2025). In chemistry machine learning models have been developed to detect cancers. Colorectal cancers can be detected through routine chemistry panels. Examples: These models achieve accuracy. The aMAP score and Liver Risk score are calculated using intelligence to determine the likelihood of liver cancer in vivo. This enables early intervention and improved outcomes (Aboulsoud et al. n.d.). The use of artificial intelligence modeling in hematology assists in risk stratification, particularly for heart failure and acute myocardial infarction. Age is estimated by neural

networks through metabolic and hematological profiles. It provides information about an individual's health after they reach their adult age (Altememi et al. 2026b).

Microbiology and Infectious Disease

Deep convolutional neural networks are particularly adept at identifying bacteria from Gram-stained preparations in microbiology and infectious disease domains. Deep convolutional neural networks are capable of accomplishing this with proficiency. With machine learning, malaria detection is accurate to a degree where it exceeds 95 percent. Identifying protozoa in stool preparations is an effective technique with deep learning capabilities. This technique enables doctors to diagnose and treat diseases with speed and accuracy, and also allows for timely treatment (Mathison n.d.). Molecular biology advances with the creation of the EVE algorithm. It can accurately forecast the variants that are likely to cause problems. The EVE algorithm examines the conservation of sequences across thousands of species. It enables physicians to classify variants with greater precision.' It assists them in making decisions regarding the treatment of genetic disorders (Aradhya et al. 2023). Artificial intelligence can be used with smartphone technology to detect malaria with a degree of accuracy. This is done using optical attachments (Weissman 2025). Predictive maintenance algorithms can also reduce the amount of time that devices are not working by 20 percent. This means that point-of-care testing resources are always available. These new capabilities have shown that they can make a difference. For example, deep learning CNN has reduced positives by 5.7 percent and false negatives by 9.4 percent for breast cancer detection. Deep learning CNN is a type of convolutional neural network. It has also been shown that artificial intelligence can detect pneumonia with 96 percent sensitivity, which's better than human radiologists. Artificial intelligence can also do a job, then expert physicians when it comes to warfarin dosing. This has been shown in a study of 19,719 patients. Additionally, predictive artificial intelligence has reduced sepsis mortality by 18 percent. This is an improvement (Becker et al. 2026).

Laboratory Professionals Survey

A survey of 342 laboratory professionals done by Siddiqui and colleagues in 2025 found that most laboratory professionals know about intelligence. However, few laboratory professionals really understand the parts of artificial intelligence. Laboratory professionals are excited about using intelligence in their work. They are worried about keeping patient data private and making sure patients get the care that is right for them. They are also worried that artificial intelligence might take their jobs. The survey by Siddiqui and colleagues in 2025 showed that laboratory professionals like the idea of using intelligence (Siddiqui et al. 2025). They want to make sure it does not hurt patient

care. Another study by Aboulsoud and colleagues in 2025 found that 22.7 percent of artificial intelligence studies in laboratory medicine check to see if their results are true in the real world. This means that most of the results might not be useful in hospitals and clinics. Most studies of intelligence in laboratory medicine look at how well it works. They do not think about how much it costs. The situation is problematic in areas with limited financial resources. It is important to consider the cost of intelligence when making decisions. Studies have failed to examine the long-term operation of artificial intelligence systems. It's challenging to determine if the systems require more maintenance and deteriorate over time (Aboulsoud et al. n.d.). Artificial intelligence systems are not often tested with kinds of patients. This can be a problem because artificial intelligence can be biased. This bias can make health disparities worse (Nicora et al. 2022). There are instances where algorithms can cause more harm than good to certain patients. This is a safety concern. Our focus should be on being cautious and ensuring the fair use of artificial intelligence for all patients. It is crucial to utilize intelligence in laboratory medicine. Our patients should be able to use it without any negative consequences (Bellini et al. 2022).

Implementation Challenges

Despite everyone knowing about workforce issues not enough studies have been done on the ways to train lab professionals to work with artificial intelligence systems. Also the many different lab information systems and old infrastructure make it hard to integrate everything, which causes problems with getting data and implementing systems. Artificial intelligence has shown to be really helpful in all research areas (Bellini et al. 2022). With its diagnostic accuracy of over 90 percent, the system can reduce errors by 30 to 50 percent and increase turnaround times by 23 to 60 percent. The reliability of results is increased by 25 percent in artificial intelligence. Artificial intelligence is utilized in chemistry to detect cancer early and detect gastric and colorectal cancers with precision. Artificial intelligence is also utilized for risk stratification. Laboratory scientists in hematology use intelligence to analyze blood samples, count cells and estimate biological age using intelligence (Zhu n.d.). Artificial intelligence improves the speed of counting cells. Microbiology utilizes artificial intelligence to categorize bacteria and identify parasites, which is essential for detecting malaria. Plasmodium is highly effective in detection. Genome science employs artificial intelligence to categorize variants and identify their potential harm. Additionally, this helps interpret information better. Smartphones are able to use artificial intelligence for point-of-care testing and predictive maintenance.

Explainable Artificial Intelligence

Artificial Intelligence understand by people is a deal. It helps make Artificial Intelligence predictions more clear and easy to grasp. There are methods like SHAP and LIME that give doctors explanations of Artificial Intelligence predictions that they can actually understand (Spies et al. 2024). These justifications may cause Artificial Intelligence to operate at a slightly slower pace. These tools are advantageous for physicians and increase their confidence in Artificial Intelligence. Federated learning serves as another avenue for improving Artificial Intelligence. Each hospital makes its model and they only share the important parts, not the actual patient data. This way they can keep data safe and it is really good for medical applications where privacy is important. There is also something called the Green Artificial Intelligence framework. It is about measuring how much energy Artificial Intelligence uses and being honest about it. This helps people make choices about Artificial Intelligence that do not hurt the environment. It is good for healthcare and for the planet. In the future Artificial Intelligence will be able to use all kinds of data like lab results, pictures from scans, genetic information and even data, from devices. This will give doctors a picture of a patient's health and help them predict what might happen with a disease. Artificial Intelligence will be able to use all this data to make healthcare better and more accurate (Xie, Zhang, and Wilson 2024).

Future of AI in Laboratories (2050 Vision)

Khokhar and his team think that by 2050 artificial intelligence will help labs work on their own. They imagine labs using intelligence to detect diseases before people show symptoms. The key features of these labs will include: Continuous health monitoring through built-in sensors and regular lab tests, intelligence helping to spot patterns for early disease detection, Robots handling samples with little human help, Real-time analysis of genomic and proteomic data and global sharing of data to improve model training and health equality (Khokhar et al. n.d.). The problem is that labs vary in their practices, materials and equipment. This results in data being collected. When data collection is incomplete it limits how well artificial intelligence models can be trained. So making data collection and lab practices standard is crucial for creating reliable artificial intelligence systems. A lot of artificial intelligence models that are being tested lack a clear understanding of how they make decisions. This insufficient transparency makes it difficult for clinicians to trust them. It creates obstacles in obtaining approval and determining liability. Artificial intelligence models' decision-making is dependent on their ability to explain them better in clinics. Why? In order to implement intelligence tools, it is necessary to integrate them with lab information systems, hospital information system, and electronic health records (Jackson et al. 2025). The complexity

of integration is attributed to the presence of numerous systems and outdated infrastructure.

Regulatory Frameworks

The rules that the Food and Drug Administration and other groups have to follow are different in places. This makes it hard for artificial intelligence to be used in devices all over the world. The Food and Drug Administration has its own way of doing things and the European Union has the Artificial Intelligence Act (Jackson et al. 2025). Artificial Intelligence requires a significant amount of data to function. Patients are often identified through personal information in this data. The problem arises due to the requirement of using this data for research purposes. We must adhere to the guidelines set forth in the Health Insurance Portability and Accountability Act and the General Data Protection Regulation regarding the protection of personal information. Artificial Intelligence models can be trained on data from healthcare, which could perpetuate existing biases and exacerbate health disparities among different populations. Healthcare applications of Artificial Intelligence are incredibly expensive (Frade et al. 2025). This can pose a challenge for laboratories and healthcare systems in countries with limited financial resources. The differences in health between poor countries may be exacerbated by this. Many people are familiar with Artificial Intelligence. A small number of people lack the technical expertise to make it function. The use of Artificial Intelligence in healthcare is often unsuccessful due to this reason. To make use of Artificial Intelligence, it is recommended to test the tools with data from nearby patients in clinics. The use of negative predictive values and other measures should be considered in addition to the Area Under the Receiver Operating Characteristic Curve. We need to establish guidelines for when the output from Artificial Intelligence should be examined by a human expert. To identify any potential issues, we must closely monitor the operation of Artificial Intelligence after it has been deployed. To avoid problems, we can use Artificial Intelligence to forecast the need for maintenance of medical instruments (Jackson et al. 2025).

Recommendations

Regulatory Recommendations

Regulatory recommendations include: Developing rules for AI to CLIA, making sure someone is responsible for AI, setting quality requirements based on risk, Checking AI tools at each place, Testing AI diagnostic tools outside, being stricter with AI tools based on their risk level and paying for AI tools based on their value (Jackson et al. 2025).

Research Priorities

Research priorities include: Checking AI studies before they are published, studying if AI tools are cost-effective, Making AI methods that can be understood, Making AI systems use energy.

Education and Training Recommendations

Education and training recommendations include: Teaching AI basics to lab professionals, Providing AI training, for lab professionals, having lab professionals, computer scientists, data scientists and bioethicists work together and AI is meant to help lab professionals not replace them (Bietenbeck and Stretcher 2021).

Multi-Criteria Decision Making Analysis

A healthcare organization wanted to choose the artificial intelligence model. They looked at three options: A1 which's a CNN, A2 which is a Random Forest and A3 which is a SVM. They considered three things when making their decision: how accurate the model is, how much it costs and how fast it works. The organization thought accuracy was the important so they gave it a weight of 0.4. Cost was next with a weight of 0.3 and speed was also important with a weight of 0.3. The organization found out that A1 was very accurate with a score of 90. It was a bit expensive with a cost of 7 and it was not the fastest with a speed of 8. A2 was not as accurate with a score of 85. It was cheaper with a cost of 5 and it was fairly fast with a speed of 7. A3 was pretty accurate with a score of 88 and its cost was 6 and it was the fastest with a speed of 9. To make a decision the organization used the TOPSIS method. This method helps them compare the options. All the scores were made comparable by normalizing their matrix after computation. Each score was divided by the root of the squares of all the accuracy scores to determine its accuracy. Their decision was based on both price and speed. When the scores were normalized, the organization obtained A1 with an accuracy of 0.592, a cost value of 0.666, and opportune speed equivalent of 0.574. A2 achieved a speed of 0.503, with an accuracy rate of only 0.477 and an error rate at 0.703. With a speed of 0.646, A3 had an accuracy of 0.5779. The organization subsequently applied the weights they had previously selected. They were provided with the weighted matrix through this. A1's accuracy was 0.237, while its cost was 0.200 and its speed was 0.172. A2's accuracy, cost, and speed were 0.151 and 0.224, respectively. The accuracy of A3 was 0.232, while its cost and speed were 0.172 and 0.194. Additionally, the organization derived the ideal solution, which is the most favorable option, and the least desirable solution. If the answer is positive, $A^+ = (0.237 \text{ and } 0.143)$ would be considered a positive value. 0.194). For example, an ideal solution with a negative value was $A^- = (0.224, 0.200, 0.151)$. After that, they computed separation measures that demonstrate how far each alternative

differs from the negative ideal solutions. $S1^+ = 0.061$ and $S1^- = 0.25$ for A1. The ideal solution's separation from the negative solution was determined by an equation. The ideal solution and the negative one were two different measures, with A2 exhibiting a separation of $S = 0.057$ and $A2^- = 0.045$. A3 had a separation of $S3^+ = 0.029$ and $S3^- = 0.02$. Ultimately, the organization computed the closeness coefficients to determine how close each option was to the ideal solution. C1 was 0.29 closeness coefficient for A1, C2 was 0.256 close, and C3 had an accuracy of 0.64 for all three groups. The organization determined that A3 was the SVM Artificial Intelligence model, followed by A2 was based on the Random Forest Artificial Intelligence model and A1 was named CNN artificial intelligence model.

To determine the accuracy of AI models using a VIKOR method, the values are calculated as best and worst (90/85) respectively. The results are presented below. By using the VIKOR method, it was determined that the cost of AI models is the lowest in terms of cost, with a value of 5 being considered the best and tenth worst. The VIKOR method was utilized to determine the optimal and ineffective speeds of AI models. The results showed a perfect value of 9 for speed and ten for rate 7 (Huang et al. 2021).

The utility measures for the AI models were calculated as $S_1 = 0.45$, $S_2 = 0.70$ and $S_3 = 0.31$ and the regret measures for the AI models were calculated as $R_1 = 0.30$, $R_2 = 0.40$ and $R_3 = 0.16$. With $S^+ = 0.31$, $S^- = 0.70$, $R^+ = 0.16$ and $R^- = 0.40$ the VIKOR indices for the AI models were calculated as $Q_1 = 0.47$, $Q_2 = 1.00$ and $Q_3 = 0.00$. The VIKOR method ranked A3 as the alternative, followed by A1 and A2. Both the TOPSIS method and the VIKOR method gave consistent results identifying A3, which is the SVM AI model as the optimal AI model for disease diagnosis. The SVM AI model achieved overall performance with high Accuracy and high Speed while maintaining reasonable Cost. This represents the balance across all decision criteria for the AI models. This application of -criteria decision-making shows how healthcare organizations can evaluate and select appropriate AI models based on multiple competing criteria for the AI models. This ensures that implementation decisions are data-driven and aligned with priorities and resource constraints, for the healthcare organizations (Huang et al. 2021).

Conclusion

Artificial intelligence is changing laboratory medicine in a way. It is making a difference in how accurately diagnoses are made how efficiently labs operate, how doctors make decisions and how patients fare. A recent review showed that artificial intelligence can achieve accuracy of over 90 percent in many cases. It can also cut down on testing by up to 50 percent. Artificial intelligence can decrease the time it takes to get test results by 23 to 60 percent. It can reduce errors that happen before tests are even run by 30

percent. Artificial intelligence can make lab results more reliable by 25 percent (Aboulsoud et al. n.d.) These are some improvements. However, there is still a gap between these results and actual use in clinics. Even though many people recognize the potential of intelligence it is not being used as much as it could be. This is because: Many research findings have not been tested enough outside of labs. Artificial intelligence is not subject to any regulations. Why? The decision-making process of artificial intelligence can be a daunting task. There is no method of gathering and disseminating data. Several lab workers are not prepared to utilize intelligence. This gap needs to be addressed in various areas. Researchers must concentrate on investigating how artificial intelligence operates in the world.'... The creation of rules by regulators should prioritize the safety of patients over other aspects. Hospitals should put their money into technology that enables AI to function without interruption. Schools must educate lab workers about the use of intelligence. Through collaboration, we can make artificial intelligence a more widely available component of laboratory medicine and improve patient care (Bietenbeck and Streichert 2021) Artificial intelligence is the future of laboratory medicine.

The introduction of artificial intelligence can initiate a period in laboratory medicine when these prerequisites are met. The focus will shift towards precise, individualized diagnostics that are accessible to everyone on the planet. Human expertise and artificial intelligence will be merged into the future laboratory. Khokhar and other experts observe that in 2025, each entity will bring their expertise to bear on the shared goal of improving patient outcomes and advancing human health. This partnership with artificial intelligence will enable early detection of diseases, improve personalized treatment, and improve population health management. The potential for intelligence in laboratory medicine is enormous (Khokhar et al. n.d.) To address the issues identified in this review, Padoan and Plebani believe that addressing these challenges in 2022 will demand significant action from all stakeholders. The year 2024 will witness the involvement of Xie and other individuals, necessitating research regulation, investment in infrastructure, and provision of comprehensive education. Through the use of artificial intelligence, we can revolutionize laboratory medicine and enhance healthcare for everyone. According to Aboulsoud and others, the implementation of this technology will ensure a safe and effective use of these technologies for patient benefit on varying levels worldwide in 2025. Jackson and others will be joining the movement in 2025, while Siddiqui and his colleagues will follow in 2030. The pursuit of integrating intelligence into laboratory medicine is still ongoing. While we have made strides, the actual realization of artificial intelligence potential will

still require us to tackle regulatory and educational issues. In 2025 and 2018, Khokhar and others advocated for the creation of a future that would bring more precision, efficiency, accessibility, and personalizedness to laboratory diagnostics. Artificial intelligence is necessary in the future to improve laboratory medicine and patient outcomes

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