



Automation and Robotics in Medical Laboratory Technology: Transforming Diagnostic Services

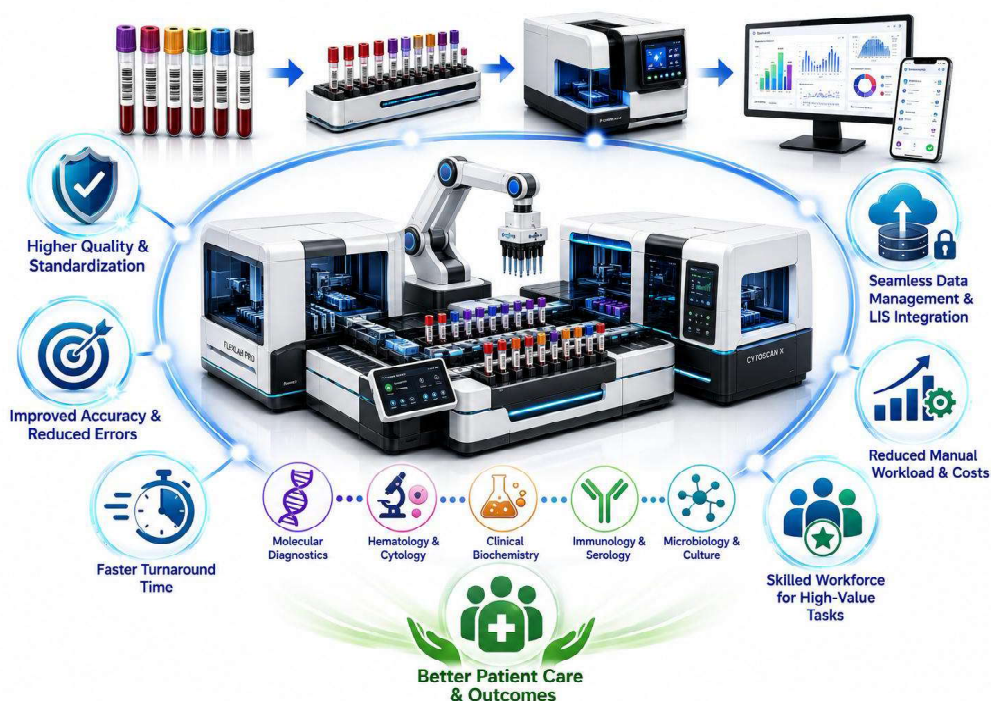
Sujit Kumar Gope¹, Avijit Ghosh¹

Department of Medical Laboratory Technology, Paramedical College Durgapur,
Bidhannagar, Durgapur, West Bengal 713212, India.

ABSTRACT

Automation and robotics are changing medical laboratory technology. They are making things faster more. More reliable. Medical labs get a lot of specimens and they need to be processed all the time. Automation and robotics help with this. They do tasks like handling samples and testing them. This means that people do not have to do these tasks. Automation and robotics also help with getting information from one place to another. This is good because it helps medical labs work better. They can get test results to patients faster. They can also make sure that the results are correct. Automation and robotics help medical lab workers focus on the tasks. To make automation and robotics work medical labs need to invest money. They need to have the equipment and trained employees. This is about how automation and robotics affecting medical labs. It is about how they're changing the way medical labs work. Automation and robotics are important for the future of labs. They will help medical labs give patients service. Medical laboratory professionals will have roles. They will be able to focus on tasks that need their skills. Automation and robotics will do the tasks. This will make medical labs better and more efficient. Automation and robotics are crucial for labs. They will make medical labs faster, safer and more reliable.

Keyword: Clinical laboratory automation; medical robotics; laboratory information systems; artificial intelligence; clinical diagnostic ;



GRAPHICAL ABSTRACT

TABLE OF CONTENTS

1. Introduction
2. Automation in Clinical Laboratory Workflows
3. Robotic System and Laboratory Information Management
4. Impact on Quality, Efficiency, and Patient Care
5. Current Challenges and Workforce Implications
6. Emerging Technologies and Future Trends
7. Conclusion

1. INTRODUCTION

Clinical diagnostic laboratories are changing fast. This is because we have a lot of tests to do and the tests are getting more complicated. We also need to get the results to the doctors. At the time we do not have enough skilled people working in the labs. So we are using automation in the labs now. Total Laboratory Automation or TLA for short is a part of this (Kim et al., 2022; Tseng et al., 2024). TLA is not about moving samples around on a conveyor belt anymore. It is a system that can do many things like getting samples ready testing them and storing them (Porto et al., 2021; Mukherjee et al., 2026). These systems can do tasks, like sorting samples spinning them down opening and closing them and moving them to the place. TLA helps make sure everything is done the way and it reduces mistakes in the lab (Brown & Badrick, 2022). This is especially important when we have a lot of samples to deal with. Even with all the automation we still need people to do some things. We need people to move samples and supplies around, load and unload machines and handle samples that're not normal. We also need people to fix problems and do tasks that're not part of the normal automation process. This is why we are developing kinds of robots like collaborative robots or autonomous mobile robots or (AMRs). These robots can do tasks in places where our normal automation systems cannot. The integration of robotics with laboratory information systems and automation platforms is a winning solution for laboratories. This indicates they can perform more efficiently and stay more linked. (Thieme et al., 2024; Xu et al., 2025). This is due to robotic systems performing tasks with precision, while laboratory information systems monitor everything efficiently. Laboratory information systems along with specialized software can oversee all these processes. Ensure that everything can be tracked. They may also concentrate on assisting patients. In the future, laboratories will likely incorporate more than just automation systems. They will utilize a combination of elements such as Total Laboratory Automation and robotic workstations. They will additionally utilize mobile platforms and intelligent software (Gruson et al., 2025). This will assist laboratories in managing high workloads with insufficient personnel. The objective is not to substitute the individuals employed in laboratories. The aim is to employ robotics to assist them and enhance the functionality of the laboratories (Jarrahi et al., 2022). In this manner, laboratories can offer services while becoming more dependable and sustainable. Robotics and lab information systems will enable this to occur.

In the future of laboratory automation, there will probably be a move away from dependence on huge, immobile automation tracks, toward a more flexible approach that includes Total Laboratory Automation, robotic work cells, autonomous mobile platforms and intelligent software. Such a hybrid approach can increase operational reliability and scalability, and help laboratories deal with increasing workloads and labour shortages. The development of safe human-robot collaboration is especially

important since the aim is to use robotics to supplement laboratory staff and not replace them, so that we can offer more effective, reliable and sustainable diagnostic services (Al Naam et al., 2022; Jarrahi et al., 2022).

2. AUTOMATION IN CLINICAL LABORATORY WORKFLOWS

Automation is now a basic part of contemporary clinical laboratory practice, especially since there has been an increase in the number of tests, more complicated diagnostic work processes, constraints on the available workforce, and the requirement for quick and reliable results. Traditional laboratory procedures usually include a number of manual stages during the pre-analytical, analytical, and post-analytical phases, which leads to the possibility of identification errors, transcription mistakes, delays, and variability (Mattiuzzi et al., 2024). The purpose of introducing automated technologies is to reduce this level of manual involvement while at the same time keeping analytical quality, specimen traceability, and patient safety. As shown in the literature reviewed, laboratory automation—particularly when combined with artificial intelligence (AI) and laboratory information systems (LIS)—is causing laboratories to change from being mainly based on manual testing to becoming interconnected and data-driven diagnostic systems (Herman et al., 2021; Hou et al., 2024). Laboratory automation today goes well beyond that offered by individual automated analyzers. Total Laboratory Automation (TLA) involves the integration of various stages in the laboratory workflow such as barcode-based specimen identification, robotic transport of specimens, automated centrifugation, sample processing, automated analysis, storage, and information management. Barcode and RFID technologies ensure reliable identification and tracking of specimens, while robotic systems enable the handling and movement of specimens between different processing stages (Gervasoni et al., 2025). Automated analyzers are capable of carrying out a large volume of testing with greater consistency, and automated storage systems allow specimens to be stored and retrieved efficiently should further or repeat testing be needed. Integration with the LIS enables the transfer and management of laboratory data and thus improves the coordination between the equipment, laboratory staff, and healthcare providers. Automation especially helps in the pre-analytical phase, as this is usually the phase with most manual work. Automated systems are capable of performing the processes of specimen identification, transportation, centrifugation, sorting and routing. Barcodes are used for sample identification and robotic management, which enhances traceability and reduces the risk of manual handling errors. The identical type of automated method can also aid haematology, microbiology, molecular diagnostics, and additional fields of the laboratory. The procedure following analysis is also increasingly backed by automation and smart information systems (Loh et al., 2022; Gül et al., 2022). Automatically moving data from the analyzers to the LIS reduces the necessity for manual entry and allows for faster result processing. This is because automated specimen handling and robotic transport remove delays that happen when people do things by hand. Getting results quickly is really important in emergency medicine, critical care and when dealing with diseases because it can affect the decisions doctors make. Automation also helps keep track of samples and reduces mistakes when writing down and identifying them, which makes patients safer and helps doctors make the diagnoses (Brown & Badrick, 2022). Using artificial intelligence with laboratory automation is a big step forward. With intelligence systems can check how well instruments are working find problems in the workflow predict when equipment needs maintenance and help figure out the best way to route specimens. If equipment is going to break down predictive maintenance can catch it before it happens and automated quality monitoring can find any problems, with test results. So smart automation can help make sure quality keeps getting better. Laboratories run smoothly. Automation also changes what laboratory personnel do. With automated systems medical laboratory professionals have time to focus on quality

understand complicated results do research fix problems and talk to doctors. This is because they do not have to do many repetitive tasks by hand. The evidence shows that artificial intelligence and automation should be used to help laboratory professionals not replace them because people are still needed to check results make sure quality is good understand findings follow rules and watch over the automated systems (Jarrahi et al., 2022; Lippi & Plebani, 2025). Laboratory automation is important and artificial intelligence helps make it better. Automation and artificial intelligence help laboratory personnel do their jobs better. Despite all the things putting in place automated lab processes needs the right setup clear rules to follow, reliable information, machines and systems that work well together strong protection against cyber threats and people who know how to use everything. The front cost of setting up these systems getting the software building the digital parts and teaching workers can be a lot, especially for smaller labs. Because of this to make automation work it's not enough to use the technology. It's also important to change the way work is done check everything is correct use quality control and keep learning and growing professionally. In the end automation in labs means moving from parts that are automated to whole systems that are connected always working and smart. Adding robots to handle samples, machines that work on their own tracking with barcodes or chips linking to lab software storing things automatically and using AI to manage work can make things faster reduce errors get results quicker and make sure the work is better and safer, for patients.

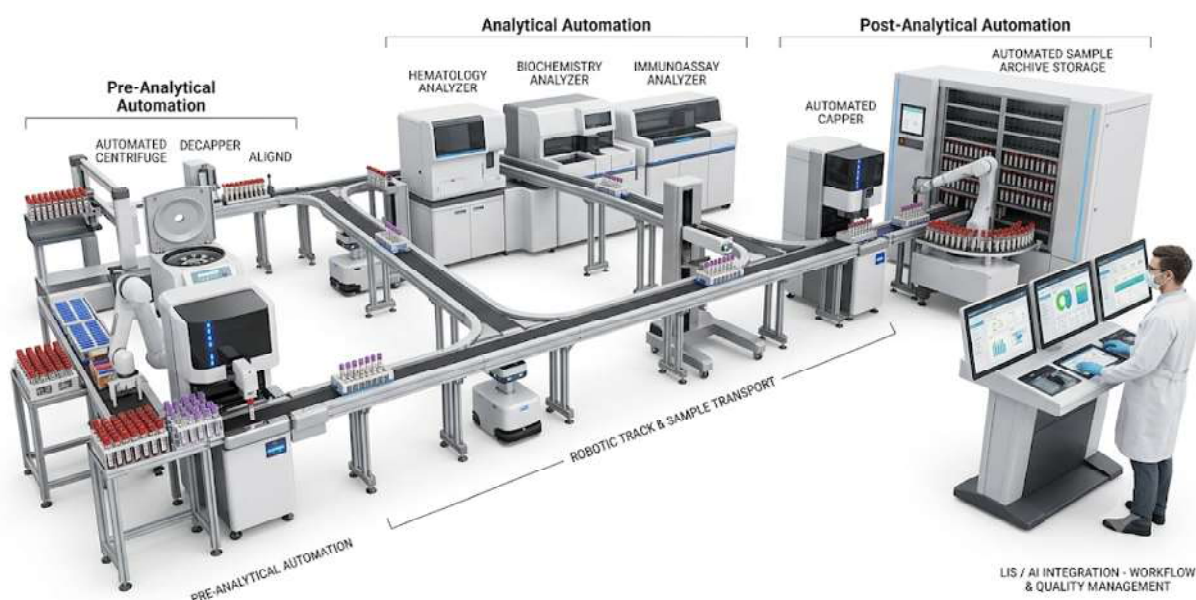


Fig. 1: Automation in laboratory workflows means putting together pre analytical, analytical and post analytical automation with robotic sample transport and a lab information system that manages the workflow.

3. ROBOTIC SYSTEMS AND LABORATORY INFORMATION MANAGEMENT

The integration of robotics with LIS has emerged as a significant advancement in contemporary clinical laboratory practices. Robotics and LIS do not qualify as systems. They collaborate to establish a link within the laboratory procedure. This involves processing specimens, examining them, overseeing specimen data, ensuring quality control, and generating reports. In the research, LIS is referred to as the “foundation” of the laboratory system since it manages all aspects of patient data, including test orders, specimens, results, and reporting. This occurs via robotics and automated systems that manage the components of lab work. Robotic tools are crucial for laboratory experiments requiring extensive repetition and duration (Schuster et al., 2024; Thieme et al., 202). In an automated lab environment,

robots can accurately perform sample sorting, pipetting, dividing samples, moving them, and managing plates. The workflow is enabled by transferring specimens between different machines. These devices consist of centrifuges, analyzers, incubators, and storage spaces. The robotic devices work well when they are connected to the Laboratory Information System (Wolf et al., 2024). For instance the automated conveyor. The machines that transport specimens can talk to the Laboratory Information System so that people can monitor everything in real time and make sure the tests are done correctly and on time. The Laboratory Information System is also very good at reducing the amount of work that people have to do to enter data. The machines that do the tests can get the information they need from the system and send the results back electronically so the people, in the laboratory do not have to keep typing everything in by hand (Falda et al., 2026; Gül et al., 2022). The system can also keep an eye on how the machines working and find any results that do not look right and it can apply the rules that have been set up before the results are given to anyone. The system can also do tests automatically if it needs to based on what the results of the first test were. This makes everything more standardized and easier to understand. Another important thing that the Laboratory Information System can do is keep track of the specimens. From the moment a specimen arrives the system pre analytical and keep a record of everything that happens to it as it goes through the laboratory. When the Laboratory Information System is used with barcodes and machines that can handle the specimens automatically it can keep a record of everything. The integration of robotics and Laboratory Information System further enhances quality management. Automated machines can do processes watch over quality control metrics and find unusual analytical situations. Laboratory Information System has the ability to save quality control information track trends. Show outcomes that are higher than set thresholds. So combining automation with information management makes a control chain from specimen identification to result reporting that is not broken. Total Laboratory Automation means an advanced version of this integration (Nam & Park, 2025). In a Total Laboratory Automation setting, , analytical and post-analytical processes are connected by conveyor systems, robotic arms, automated machines and information systems. Robotics helps with the movement of samples while Laboratory Information System manages data about test requests, specimen conditions and results. The research shows that this combined method can make turnaround time, standardization and the overall functioning of the laboratory better. Using robotic systems and Laboratory Information System also has its own set of problems. Good automation needs machines, middleware and Laboratory Information System to work and this can be hard when instruments, from different companies are used. Technical problems, software issues and device failures can stop lab activities. Also lab staff need training to watch over maintain and fix issues with automated systems. The research says that good automation needs planning, employee training and focus on system integration instead of just buying automated machines. Keeping data safe is very important because robotic platforms, machines, Laboratory Information System and hospital networks share patient and laboratory data (Pennestrì & Banfi, 2022).

4. IMPACT ON QUALITY, EFFICIENCY, AND PATIENT CARE

Automation and robotics have really improved the quality of services by making laboratory testing more precise, reliable and consistent. The old way of doing things in labs often involves doing the tasks over and over which can be affected by how tired people are, different ways of doing things and mistakes people make.

Table 1: Impact of Automation and Robotics on Quality, Efficiency, and Patient Care in Clinical Laboratory

Impact area	Function of Automation and Robotics	Impact on lab performance	Impact on patient treatment	References
Quality and precision	Automated system reduce mistakes and effectively standardize processes..	Improves reliable laboratory results	More dependable laboratory results support accurate diagnosis and treatment decisions.	(Nam & Park 2025)
Response time	Automated specimen transport, preparation, analysis, and results verification accelerate workflow.	Reduce the time between specimen and results are reported.	Faster availability of results can support earlier clinical decision-making.	(Tseng et al, 2024)
Workflow efficiency	Integration of pre-analytical, analytical, and post-analytical processes minimizes unnecessary manual steps.	Increases laboratory throughput and productivity.	Patients can receive diagnostic information more efficiently.	(Tseng et al., 2024)
Error reduction	Automated identification, sorting, aliquoting, and processing standardize repetitive procedures.	Reduces opportunities for manual processing errors.	Improved process reliability contributes to patient safety.	(Lippi et al., 2009)
Standardization	Automated systems perform procedures according to predefined protocols.	Provides greater uniformity between samples and across laboratory shifts.	Consistent testing contributes to dependable diagnostic services.	(Wanger et al, 2021)
Quality control	Real-time quality-control systems and auto-verification can be integrated with automated workflows.	Enables rapid identification of abnormal processes and supports reliable result validation.	Helps prevent inappropriate results from reaching clinicians.	(Tseng et al, 2024)

5. CURRENT CHALLENGES AND WORKFORCE IMPLEMENTATIONS

The medical laboratory is changing because of automation, robotics, laboratory information management systems and artificial intelligence. Automation can make things more efficient reduce tasks and make laboratory services faster and more consistent.. It also creates problems for the people who work in laboratories. One big worry is that automation could mean jobs because machines can do a lot of the repetitive work that people used to do. A study compared laboratories that use laboratory automation with those that do not. It found that workers were more productive in some areas, like chemistry and serology.. In other areas like hematology there was not much difference. This means that automation might reduce the number of staff needed for some tests. It could also mean that each worker can do more. We should not just think about automation as a way to cut jobs. They will also have to be able to interpret data and manage laboratory information systems. This means that laboratory workers will need a mix of new skills. They will need to know about biology and medicine. They will also need

to know about technology and information systems. The big challenge is not about reducing manual work but also about preparing laboratory professionals for more complex and technical roles. Laboratory professionals will have to learn things like how to work with automation and laboratory information management systems. This will help them to do their jobs better and to keep up with the changes, in the laboratory.

Another difficulty is the changing and hard to predict makeup of the lab team. The case study shows that in some places the number of lab workers retiring is higher than the number of graduates entering the field even as the amount of work for labs goes up. Automation can help in some ways by letting labs handle tests with fewer people. Relying too much on automated systems can cause problems. It might make people depend much on technology and cause some traditional lab skills to fade away. This means there needs to be a balance between using automation and using human skills especially because making the right decisions is very important when tools give strange or unexpected results (Jarrahi et al., 2022). A big problem is the gap in knowledge caused by changes in technology. Lab workers need to keep learning because of things like automation, AI, robots, digital pathology, molecular testing and LIMS. The second review sent in talks about problems with skills because of automation and not having training programs. It says that lab workers today need a range of skills instead of just using old lab methods. Not being ready for these changes can cause resistance to technology not using equipment properly and lower confidence among workers. The research also says that some labs don't have training for their staff not enough help, with IT and not enough technical support. This leads to not using automated tools using them wrong or having them fail. The case study shows clearly that putting in TLA means changing lab spaces and teaching workers skills. The same review of how people're managed talks about problems like not enough space, not enough money, limited chances to keep learning and trouble getting help to fix equipment in places that don't have much. These issues can make automation less effective. Can cause more problems when things go wrong. Changing the people who work in labs is a part of making automation work well. Continuous learning updating skills learning across areas getting advice and taking online classes can help lab workers get ready for new jobs. The research shows that training programs focused on automation and organized continuing education can help people improve their skills in lab software, AI, digital tools and new areas. The case study also says that retraining and learning are important in labs so workers can get skills that are useful, for AI and lab software. For BMLT workers this means that future training should mix lab methods with using machines solving problems checking quality, basic data analysis, LIS/LIMS systems and digital lab tools.

The examination of workplace management addresses issues such as employees being laid off, outdated skills losing relevance, the emotions workers experience when collaborating with machines, and certain employees resisting change. The individuals overseeing the laboratory need to collaborate with their team to modify work processes and clearly communicate how roles will evolve. Effective methods for achieving this involve implementing new technology, training individuals in a mix of traditional and modern skills, and alternating between machine work and manual tasks. This can assist in maintaining employee engagement and flexibility. Considerations should also include leadership, communication, and workforce planning. Automation transforms the methods of performing tasks. The evaluation of workforce management indicates that strategizing for ongoing professional development, training employees for diverse roles, providing mentoring, and utilizing laboratory information management systems can enhance worker efficiency and minimize errors.

6. EMERGING TECHNOLOGIES AND FUTURE TRENDS

Medical laboratory technology is going to change a lot because of technologies. These new technologies include robotics, artificial intelligence, machine learning and digital connectivity. They will be used in laboratories that are getting smarter. The future of laboratory automation is changing. It is moving away from machines that work alone to total laboratory automation. This means that all the steps in the laboratory process will be connected. These steps include getting samples ready analyzing them and managing the results. Robots and computers will help with these steps. These systems can help reduce the amount of work people have to do. They can also help make sure that everything is done the way every time. This reduces mistakes. Makes diagnostic testing faster and more consistent. Artificial intelligence and machine learning will be important in laboratory automation. Artificial intelligence can help find patterns, in test results and spot results that're not normal. It can also help with quality control. Predict when machines might have problems. Artificial intelligence can make it easier to understand laboratory data (Paranjape *et al.*, 2021).

When artificial intelligence is used with laboratory information systems it can help validate and prioritize test results. This means that laboratory professionals can focus on the important and complicated cases. However people must still make sure that the systems are working correctly and that they are following the rules. Medical laboratory technology and artificial intelligence must be used together to improve laboratory work. Intelligence and machine learning are the future of medical laboratory technology (Herman *et al.*, 2021). The devices that are connected can send data all the time about the samples and the instruments and the things they use to do tests. They can also send data about the temperature. When things need to be fixed and how well things are working. This can help people who work in the lab know when things might break and they can fix them before that happens. It can also help them use the things in the lab better and see what is going on all the time. The Internet of Things and cloud data systems can also let people use the lab information from else.. The people in charge of the lab have to make sure the data is safe and that only the right people can see it. The lab also has to follow the rules and make sure the Internet of Things and cloud data systems work with the systems they use (Pennestrì & Banfi, 2022). The Internet of Things and cloud data systems are very important, for labs.

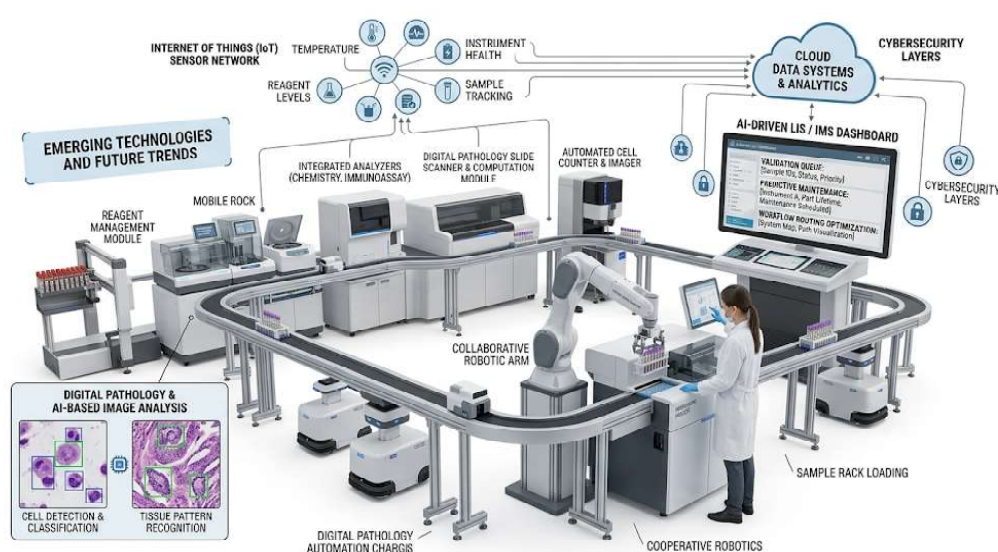


Fig. 2: Emerging technologies and future trends show that automation, in laboratory services will grow by adding IoT, artificial intelligence, digital pathology, cloud based analytics and collaborative robotics.

7. CONCLUSION

Automation and robotics are changing medical lab technology by making the speed, consistency, dependability and organization of diagnostic lab services. The mix of Total Laboratory Automation (TLA) workstations, automated analyzers, barcode specimen identification, automated centrifugation, robotic specimen transport, automated storage and Laboratory Information Systems (LIS) can connect pre-analytical, analytical and post-analytical procedures into a smooth process. These tools reduce manual work cut down on mistakes in specimen identification and handling improve tracking make the time it takes to get results shorter and help get lab results out faster. The mix of robotics with LIS makes tracking specimens watching the workflow ensuring quality and handling data better (Wolf et al., 2024).

Automation and robotics help laboratory workers by taking over repeated tasks and letting them focus on work that needs their skills, quality checks, solving problems analyzing complex results and making technical decisions. The future of lab work will involve collaboration between lab experts, robotics, automation, LIS, artificial intelligence and smart software of replacing human workers completely (Jarrahi et al., 2022; Gruson et al., 2025). Ongoing learning and training will be important for lab professionals to gain skills in automation, robotics, LIS/LIMS, data management, quality control and other digital tools.

With all these benefits putting automation into place needs careful planning because labs might face big initial costs, problems with connecting systems issues with software and hardware, cybersecurity and privacy concerns, maintenance needs and the need for trained people. Because of this automation must be used with quality control training for staff, checking systems, technical support, good workflow design and strong data protection plans. Overall automation and robotics are a direction, for the future of medical lab technology. They offer the chance to create services that are faster safer more reliable, connected, sustainable and focused on patients (Nam & Park, 2025; Mukherjee et al., 2026).

Author contribution S.K.G.: Conceptualization, Methodology, Formal analysis, Investigation , Writing Original draft ; A.G.: Visualization, Writing – review & editing .

Declaration The authors declare no conflicts of interest.

AI Disclosure Statement During the preparation of this manuscript, the authors used ChatGPT ,Gemini and quillbot for language improvement, grammar correction,image generation and enhancement of readability. The authors reviewed and edited all AI-assisted content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.

Funding This review work was not funded.

Acknowledgement None

REFERENCE

1. Aggarwal, A., Bharadwaj, S., Corredor, G., Pathak, T., Badve, S., & Madabhushi, A. (2025). Artificial intelligence in digital pathology – time for a reality check. *Nature reviews. Clinical oncology*, 22(4), 283–291. <https://doi.org/10.1038/s41571-025-00991-6>
2. Al Naam, Y. A., Elsafi, S., Al Jahdali, M. H., Al Shaman, R. S., Al-Qurouni, B. H., & Al Zahrani, E. M. (2022). The Impact of Total Automaton on the Clinical Laboratory Workforce: A Case Study. *Journal of healthcare leadership*, 14, 55–62. <https://doi.org/10.2147/JHL.S362614>

3. Baron J. M. (2023). Artificial Intelligence in the Clinical Laboratory: An Overview with Frequently Asked Questions. *Clinics in laboratory medicine*, 43(1), 1–16. <https://doi.org/10.1016/j.cll.2022.09.002>
4. Berbis, M. A., McClintock, D. S., Bychkov, A., Van der Laak, J., Pantanowitz, L., Lennerz, J. K., Cheng, J. Y., Delahunt, B., Egevad, L., Eloy, C., Farris, A. B., 3rd, Frassetto, F., García Del Moral, R., Hartman, D. J., Herrmann, M. D., Hollemans, E., Iczkowski, K. A., Karsan, A., Kriegsmann, M., Salama, M. E., ... Shen, J. (2023). Computational pathology in 2030: a Delphi study forecasting the role of AI in pathology within the next decade. *EBioMedicine*, 88, 104427. <https://doi.org/10.1016/j.ebiom.2022.104427>
5. Bridge, C. P., Gorman, C., Pieper, S., Doyle, S. W., Lennerz, J. K., Kalpathy-Cramer, J., Clunie, D. A., Fedorov, A. Y., & Herrmann, M. D. (2022). Highdicom: a Python Library for Standardized Encoding of Image Annotations and Machine Learning Model Outputs in Pathology and Radiology. *Journal of digital imaging*, 35(6), 1719–1737. <https://doi.org/10.1007/s10278-022-00683-y>
6. Brown, A. S., & Badrick, T. (2022). The next wave of innovation in laboratory automation: systems for auto-verification, quality control and specimen quality assurance. *Clinical chemistry and laboratory medicine*, 61(1), 37–43. <https://doi.org/10.1515/cclm-2022-0409>
7. Bunch, D. R., Durant, T. J., & Rudolf, J. W. (2023). Artificial Intelligence Applications in Clinical Chemistry. *Clinics in laboratory medicine*, 43(1), 47–69. <https://doi.org/10.1016/j.cll.2022.09.005>
8. Bruce, C., Prassas, I., Mokhtar, M., Clarke, B., Youssef, E., Wang, C., & Yousef, G. M. (2024). Transforming diagnostics: The implementation of digital pathology in clinical laboratories. *Histopathology*, 85(2), 207–214. <https://doi.org/10.1111/his.15178>
9. Cherkaoui, A., & Schrenzel, J. (2022). Total Laboratory Automation for Rapid Detection and Identification of Microorganisms and Their Antimicrobial Resistance Profiles. *Frontiers in cellular and infection microbiology*, 12, 807668. <https://doi.org/10.3389/fcimb.2022.807668>
10. Cintrón, M., Clark, B., Miranda, E., & Babady, N. E. (2025). Utility of digital images captured after 4 h of incubation on a microbiology laboratory automation system in guiding the work-up of subcultures from positive blood cultures. *Journal of clinical microbiology*, 63(2), e0132024. <https://doi.org/10.1128/jcm.01320-24>
11. Dawson H. (2022). Digital pathology - Rising to the challenge. *Frontiers in medicine*, 9, 888896. <https://doi.org/10.3389/fmed.2022.888896>
12. De Iuliis, V., & Chiatamone Ranieri, S. (2026). Performance Evaluation of the Scpio Labs X100HT Digital Morphology Analyzer and Abnormal Cell Detection in Peripheral Blood Smears. *International journal of laboratory hematology*, 48(1), 54–62. <https://doi.org/10.1111/ijlh.70005>
13. Elie, N., Giffard, F., Blanc-Fournier, C., Morice, P. M., Brachet, P. E., Dutoit, S., Plancoulaine, B., & Poulain, L. (2022). Impact of automated methods for quantitative evaluation of immunostaining: Towards digital pathology. *Frontiers in oncology*, 12, 931035. <https://doi.org/10.3389/fonc.2022.931035>
14. Eloy, C., Vale, J., Curado, M., Polónia, A., Campelos, S., Caramelo, A., Sousa, R., & Sobrinho-Simões, M. (2021). Digital Pathology Workflow Implementation at IPATIMUP. *Diagnostics (Basel, Switzerland)*, 11(11), 2111. <https://doi.org/10.3390/diagnostics11112111>
15. Falda, A., Bernardi, D., Moz, S., Mion, M. M., Stefani, A., Sciacovelli, L., Basso, D., & Montagnana, M. (2026). A model to increase automation and support reliable interpretation of clinical chemistry tests. *Clinical chemistry and laboratory medicine*, 64(9), 2026–2035. <https://doi.org/10.1515/cclm-2025-1727>
16. Falvella, F. S., Chibireva, M., & Panteghini, M. (2021). Prospective validation of an automatic reflex test for identifying spurious elevations of mean corpuscular haemoglobin concentration due to the presence of cold agglutinins. *Scandinavian journal of clinical and laboratory investigation*, 81(7), 598–600. <https://doi.org/10.1080/00365513.2021.1959051>
17. Gervasoni, J., Pedrazzini, D., Cicchinelli, M., Persichilli, S., Baroni, S., Rocchetti, S., Arcuri, G., & Urbani, A. (2025). Impact of an autonomous delivery robot on sample turnaround time in a clinical laboratory: an early evaluation of first implementation. *Clinical chemistry and laboratory medicine*, 64(4), 832–837. <https://doi.org/10.1515/cclm-2025-1336>
18. Grisi, C., Kartasalo, K., Eklund, M., Egevad, L., van der Laak, J., & Litjens, G. (2025). Hierarchical Vision Transformers for prostate biopsy grading: Towards bridging the generalization gap. *Medical image analysis*, 105, 103663. <https://doi.org/10.1016/j.media.2025.103663>

19. Gruson, D., Gouget, B., Lee, W., Greaves, R., Liu, Y., Ebert, S., Yang, H. S., & Shah, S. (2025). From automation to agentic artificial intelligence in laboratory medicine: an opinion of the IFCC Division on Emerging Technologies. *Clinical chemistry and laboratory medicine*, 64(5), 985–988. <https://doi.org/10.1515/cclm-2025-1314>
20. Herman, D. S., Rhoads, D. D., Schulz, W. L., & Durant, T. J. S. (2021). Artificial Intelligence and Mapping a New Direction in Laboratory Medicine: A Review. *Clinical chemistry*, 67(11), 1466–1482. <https://doi.org/10.1093/clinchem/hvab165>
21. Herbst, H., & Pocha, K. (2026). Automation of a pathology laboratory - current developments. *Automatisierung eines Pathologie-Labors – aktuelle Entwicklungen*. *Pathologie (Heidelberg, Germany)*, 47(Suppl 1), 32–38. <https://doi.org/10.1007/s00292-025-01512-z>
22. Huang, P., Lan, H., Liu, B., Mo, Y., Gao, Z., Ye, H., & Pan, T. (2025). Transformative laboratory medicine enabled by microfluidic automation and artificial intelligence. *Biosensors & bioelectronics*, 271, 117046. <https://doi.org/10.1016/j.bios.2024.117046>
23. Jarrahi, M. H., Davoudi, V., & Haeri, M. (2022). The key to an effective AI-powered digital pathology: Establishing a symbiotic workflow between pathologists and machine. *Journal of pathology informatics*, 13, 100156. <https://doi.org/10.1016/j.jpi.2022.100156>
24. Khan, A., Janowczyk, A., Müller, F., Blank, A., Nguyen, H. G., Abbet, C., Studer, L., Lugli, A., Dawson, H., Thiran, J. P., & Zlobec, I. (2022). Impact of scanner variability on lymph node segmentation in computational pathology. *Journal of pathology informatics*, 13, 100127. <https://doi.org/10.1016/j.jpi.2022.100127>
25. Kim, H., Hur, M., d’Onofrio, G., & Zini, G. (2025). Real-World Application of Digital Morphology Analyzers: Practical Issues and Challenges in Clinical Laboratories. *Diagnostics (Basel, Switzerland)*, 15(6), 677. <https://doi.org/10.3390/diagnostics15060677>
26. Kim, K., Lee, S. G., Kim, T. H., & Lee, S. G. (2022). Economic Evaluation of Total Laboratory Automation in the Clinical Laboratory of a Tertiary Care Hospital. *Annals of laboratory medicine*, 42(1), 89–95. <https://doi.org/10.3343/alm.2022.42.1.89>
27. Antonios, K., Croxatto, A., & Culbreath, K. (2021). Current State of Laboratory Automation in Clinical Microbiology Laboratory. *Clinical chemistry*, 68(1), 99–114. <https://doi.org/10.1093/clinchem/hvab242>
28. Kritikos, A., Prod’hom, G., Jacot, D., Croxatto, A., & Greub, G. (2024). The Impact of Laboratory Automation on the Time to Urine Microbiological Results: A Five-Year Retrospective Study. *Diagnostics (Basel, Switzerland)*, 14(13), 1392. <https://doi.org/10.3390/diagnostics14131392>
29. Liao, H., Zhang, F., Chen, F., Li, Y., Sun, Y., Sloboda, D. D., Zheng, Q., Ying, B., & Hu, T. (2025). Application of artificial intelligence in laboratory hematology: Advances, challenges, and prospects. *Acta pharmaceutica Sinica. B*, 15(11), 5702–5733. <https://doi.org/10.1016/j.apsb.2025.05.036>
30. Lippi, G., & Plebani, M. (2025). Lights and shadows of artificial intelligence in laboratory medicine. *Advances in laboratory medicine*, 6(1), 1–3. <https://doi.org/10.1515/almed-2025-0024>
31. Mattiuzzi, C., Lippi, G & Favaloro, E. J. (2024). Artificial intelligence in the pre-analytical phase: State-of-the art and future perspectives. *Journal of medical biochemistry*, 43(1), 1–10. <https://doi.org/10.5937/jomb0-45936>
32. Loh, T. P., Tan, R. Z., Lim, C. Y., & Markus, C. (2022). An Objective Approach to Deriving the Clinical Performance of Autoverification Limits. *Annals of laboratory medicine*, 42(5), 597–601. <https://doi.org/10.3343/alm.2022.42.5.597>
33. Lu, M. Y., Chen, R. J., Kong, D., Lipkova, J., Singh, R., Williamson, D. F. K., Chen, T. Y., & Mahmood, F. (2022). Federated learning for computational pathology on gigapixel whole slide images. *Medical image analysis*, 76, 102298. <https://doi.org/10.1016/j.media.2021.102298>
34. Makhlouf, Y., Salto-Tellez, M., James, J., O’Reilly, P., & Maxwell, P. (2022). General Roadmap and Core Steps for the Development of AI Tools in Digital Pathology. *Diagnostics (Basel, Switzerland)*, 12(5), 1272. <https://doi.org/10.3390/diagnostics12051272>
35. Nam, Y., & Park, H. D. (2025). Revolutionizing Laboratory Practices: Pioneering Trends in Total Laboratory Automation. *Annals of laboratory medicine*, 45(5), 472–483. <https://doi.org/10.3343/alm.2024.0581>
36. Paranjape, K., Schinkel, M., Hammer, R. D., Schouten, B., Nannan Panday, R. S., Elbers, P. W. G., Kramer, M. H. H., & Nanayakkara, P. (2021). The Value of Artificial Intelligence in Laboratory Medicine. *American journal of clinical pathology*, 155(6), 823–831. <https://doi.org/10.1093/ajcp/aqaa170>

37. Pasqualetti, S., Carnevale, A., Dolci, A., & Panteghini, M. (2022). A step towards optimal efficiency of HbA1c measurement as a first-line laboratory test: the TOP-HOLE (Towards Optimal glycoHemOgLobin tEsting) project. *Clinical chemistry and laboratory medicine*, 60(3), 441–450. <https://doi.org/10.1515/cclm-2021-1249>
38. Pennestrì, F., & Banfi, G. (2022). Artificial intelligence in laboratory medicine: fundamental ethical issues and normative key-points. *Clinical chemistry and laboratory medicine*, 60(12), 1867–1874. <https://doi.org/10.1515/cclm-2022-0096>
39. Porto, L. F. B., Franca, C. N., & Ferreira, C. E. D. S. (2021). Principles for Organizing the Flow of Automation in the Clinical Laboratory. *Clinical laboratory*, 67(7), 10.7754/Clin.Lab.2020.201102. <https://doi.org/10.7754/Clin.Lab.2020.201102>
40. Rahaman, M. M., Millar, E. K. A., & Meijering, E. (2025). Generalized deep learning for histopathology image classification using supervised contrastive learning. *Journal of advanced research*, 75, 389–404. <https://doi.org/10.1016/j.jare.2024.11.013>
41. Romanchikova, M., Thomas, S. A., Dexter, A., Shaw, M., Partarrieau, I., Smith, N., Venton, J., Adeogun, M., Brettle, D., & Turpin, R. J. (2022). The need for measurement science in digital pathology. *Journal of pathology informatics*, 13, 100157. <https://doi.org/10.1016/j.jpi.2022.100157>
42. Ronzio, L., Cabitza, F., Barbaro, A., & Banfi, G. (2021). Has the Flood Entered the Basement? A Systematic Literature Review about Machine Learning in Laboratory Medicine. *Diagnostics (Basel, Switzerland)*, 11(2), 372. <https://doi.org/10.3390/diagnostics11020372>
43. Rupp, N., Ries, R., Wienbruch, R., & Zuchner, T. (2024). Can I benefit from laboratory automation? A decision aid for the successful introduction of laboratory automation. *Analytical and bioanalytical chemistry*, 416(1), 5–19. <https://doi.org/10.1007/s00216-023-05038-2>
44. Schuster, J., Kamuju, V., Zhou, J., & Mathaes, R. (2024). Piston-driven automated liquid handlers. *SLAS technology*, 29(3), 100128. <https://doi.org/10.1016/j.slant.2024.100128>
45. Sudin, E., Searjeant, M., Partridge, G., Phillips, P., Hiller, L., Snead, D., Ellis, I., & Chen, Y. (2022). Digital pathology: the effect of experience on visual search behavior. *Journal of medical imaging (Bellingham, Wash.)*, 9(3), 035501. <https://doi.org/10.1117/1.JMI.9.3.035501>
46. Tan-Garcia, A., Chua, T. H., & Leow, W. Q. (2025). Computational pathology in the age of artificial intelligence – embrace not fear. *The journal of pathology. Clinical research*, 11(5), e70049. <https://doi.org/10.1002/2056-4538.70049>
47. Thieme, A., Renwick, S., Marschmann, M., Guimaraes, P. I., Weissenborn, S., & Clifton, J. (2024). Deep integration of low-cost liquid handling robots in an industrial pharmaceutical development environment. *SLAS technology*, 29(5), 100180. <https://doi.org/10.1016/j.slant.2024.100180>
48. Tseng, C. W., Li, Y. C., Lee, H. S., & Tseng, Y. M. (2024). Laboratory testing consolidation and total laboratory automation improves service efficiency and effectiveness: a study of a medical center in Taiwan. *Laboratory medicine*, 55(6), 677–685. <https://doi.org/10.1093/labmed/lmae044>
49. van der Laak, J., Litjens, G., & Ciompi, F. (2021). Deep learning in histopathology: the path to the clinic. *Nature medicine*, 27(5), 775–784. <https://doi.org/10.1038/s41591-021-01343-4>
50. Wagner, S. J., Matek, C., Shetab Boushehri, S., Boxberg, M., Lamm, L., Sadafi, A., Waibel, D. J. E., Marr, C., & Peng, T. (2022). Make deep learning algorithms in computational pathology more reproducible and reusable. *Nature medicine*, 28(9), 1744–1746. <https://doi.org/10.1038/s41591-022-01905-0>
51. Wolf, Á., Zsoldos, P., Széll, K., & Galambos, P. (2024). Towards robotic laboratory automation plug & play: Reference architecture model for robot integration. *SLAS technology*, 29(4), 100168. <https://doi.org/10.1016/j.slant.2024.100168>
52. Gül, B. Ü., Özcan, O., Doğan, S., & Arpacı, A. (2022). Designing and validating an autoverification system of biochemical test results in Hatay Mustafa Kemal University, clinical laboratory. *Biochemia medica*, 32(3), 030704. <https://doi.org/10.11613/BM.2022.030704>
53. Makhoul, H. R., Ossandon, M. R., Farahani, K., Lubensky, I., & Harris, L. N. (2025). Digital pathology imaging artificial intelligence in cancer research and clinical trials: An NCI workshop report. *Journal of pathology informatics*, 20, 100531. <https://doi.org/10.1016/j.jpi.2025.100531>
54. Dey P. (2025). A Critical Review of Deep Learning Technique and Its Applications in Clinical Cytology. *Journal of cytology*, 42(4), 185–198. https://doi.org/10.4103/joc.joc_136_25

55. Schwen, L. O., Kiehl, T. R., Carvalho, R., Zerbe, N., & Homeyer, A. (2023). Digitization of Pathology Labs: A Review of Lessons Learned. *Laboratory investigation; a journal of technical methods and pathology*, 103(11), 100244. <https://doi.org/10.1016/j.labinv.2023.100244>
56. Munari, E., Scarpa, A., Cima, L., Pozzi, M., Pagni, F., Vasuri, F., Marletta, S., Dei Tos, A. P., & Eccher, A. (2024). Cutting-edge technology and automation in the pathology laboratory. *Virchows Archiv : an international journal of pathology*, 484(4), 555–566. <https://doi.org/10.1007/s00428-023-03637-z>
57. Herbst, H., Rüdiger, T., & Hofmann, C. (2022). Automatisierung und Einsatz von Robotern im Pathologielabor [Automation and application of robotics in the pathology laboratory]. *Der Pathologe*, 43(3), 210–217. <https://doi.org/10.1007/s00292-022-01073-5>
58. Mukherjee, S., Lambert, C., Zhou, Y., Kan, S., Yang, J., Liao, G., Flygare, S., & Ohgami, R. S. (2026). Collaborative Robotics, Mobile Platforms, and Total Laboratory Automation in Clinical Diagnostics. *Diagnostics (Basel, Switzerland)*, 16(4), 518. <https://doi.org/10.3390/diagnostics16040518>
59. Xu, J., Deng, P., Matthews, K., Duffy, S. P., & Ma, H. (2025). Vibration-Assisted Magnetic (VibroMag) Cell Separation for Robotic Liquid Handling Platforms. *Analytical chemistry*, 97(42), 23449–23456. <https://doi.org/10.1021/acs.analchem.5c04557>
60. Schuster, J., Kamuju, V., Zhou, J., & Mathaes, R. (2024). Piston-driven automated liquid handlers. *SLAS technology*, 29(3), 100128. <https://doi.org/10.1016/j.slas.2024.100128>