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Review Article

Robotic Laboratory Automation: A Scoping Review of Feasibility, Costing, Planning, and Design Strategies

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ABSTRACT

Introduction Automated robotic laboratory systems bring together robotics artificial intelligence, and informatics to support various laboratory processes. This scoping review aimed to map the extent, nature, and distribution of published evidence on the feasibility, costing, planning, and designing of these systems.

Methods The review was conducted according to Joanna Briggs Institute methodology and PRISMA-ScR guidelines. The review included any type of laboratory (population), automated robotic technologies used in laboratory work (concept), and aspects related to feasibility, costing, planning, or designing (context). We searched PubMed, MEDLINE via PubMed and Embase for English-language peer-reviewed articles published after 2015. Two independent reviewers screened 509 records using Rayyan software. Fifteen studies ultimately met the inclusion criteria. Data were charted and synthesised thematically.

Results The included studies consisted of case studies, quantitative evaluations, mixed-methods analyses, and reviews from the fields of clinical microbiology, pathology, chemistry, and general laboratory automation. These studies represented settings in India, North America, Europe, and Asia. Evidence on feasibility highlighted track-based systems, integration of AI with Internet of Things, decision tree approaches suitable for smaller laboratories, and advanced concepts such as knowledge graphs and digital twins. Costing studies emphasised the importance of full life-cycle costing models that consider maintenance and reagents, demonstrating that return on investment is often achieved through labour savings and reduced errors. Planning recommendations focused on interdisciplinary collaboration, use of decision-support tools, lean improvement events, and standardising chain-of-custody processes. Designing findings pointed to modular platforms, collaborative robots, user-programmable interfaces, and effective integration of liquid handlers with analytical software.

Conclusion The evidence shows meaningful improvements in turnaround time and laboratory throughput, particularly in high-volume settings. However, significant gaps remain, especially in low- and middle-income countries, long-term costing data, and evaluations of emerging fully autonomous systems. Future research should focus on multi-centre studies and the development of practical planning frameworks to support more equitable and effective adoption of robotic laboratory automation.

Keywords*: Robotic laboratory automation, Total laboratory automation, Feasibility assessment, Cost analysis, Implementation planning, Laboratory system design*

INTRODUCTION

Automated robotic laboratory systems represent a transformative advancement in scientific research and diagnostics, integrating robotics, artificial intelligence, and automation to enhance efficiency, accuracy, and throughput in laboratory environments. These systems are increasingly adopted in fields such as biomedical research, pharmaceutical development, clinical diagnostics, and environmental testing. They include technologies like robotic pipetting stations, automated sample handlers, high-throughput screening platforms, and fully integrated lab-on-a-chip systems [1].

In the contemporary landscape of clinical diagnostics, total laboratory automation (TLA) systems represent a paradigm shift toward enhanced operational efficacy, error mitigation, and resource optimisation within healthcare institutions. By integrating automated pre-analytical processing, analytical instrumentation, and post-analytical informatics, TLA facilitates streamlined workflows that address escalating demands for diagnostic throughput. This article synthesises empirical evidence from 18 white papers across diverse global healthcare settings, encompassing public hospitals, private reference laboratories, and specialised facilities. The analysis elucidates key performance indicators such as turnaround time, test volume scalability, staff productivity, and quality assurance, while critically appraising contextual dependencies. For hospital administrators, these insights underscore strategic considerations for TLA adoption, balancing potential efficiencies against institutional-specific variables to inform decision-making in resource-constrained environments [2].

In a tertiary Care Hospital (DPLM, King Faisal Specialist Hospital & Research Centre), TLA implementation reduced overall TAT for all tests by 32% by 2016, compared to the pre-TLA baseline of 2012, with median TAT for routine glucose tests dropping from 70.1 to 55.7 minutes (a 21% reduction) [3]. In another study, it has been reported that the overall TAT for all tests was reduced by 32%. The median TAT for random glucose tests was reduced by 21% [4]. The reduction of laboratory TAT has been achieved through TLA implementations across diverse global institutions. Post-implementation, Severance Hospital (Tertiary Care, >2,300 beds) post-TLA, mean TAT for immunoassays fell by 41.2 minutes and for clinical chemistry tests by 26.0 minutes, with the 99th percentile TAT for immunoassays dropping by 200.6 minutes [5]. At the West China Hospital, Sichuan University (4,300-bed tertiary hospital, microbiology TLA), after implementing the BD Kiestra TLA platform, the median TAT for positive CSF cultures changed most significantly, from 86.76 to 64.30 hours, while overall positive culture TAT decreased from 65.93 to 63.53 hours [6].

In a study done in India, TLA Implementation led to 56% reduction in manual workflow steps and a 75% reduction in sample handling touchpoints. The proportion of samples meeting TAT targets improved across all disciplines. On the TLA line, 81–86% of chemistry tests were reported within 30 minutes, and up to 89% of high-sensitivity troponin I results were available within 40 minutes with improved process stability [7].

Human resource optimisations from total laboratory automation in global labs have resulted in freeing staff from routine tasks for value-added work. The number of tests performed by a single worker can increase between 1.4 to 3.7 times in the clinical chemistry and serology sections[8]. In a study from Saudi Arabia, staffing costs reduced by 1.14 million SAR with fewer senior staff, and there were reductions in staff at both senior and junior levels [4]. Adoption of automation can take away mundane, repetitive and manual steps, reducing errors and allowing redefinition of the job roles of skilled manpower towards value-added activities such as quality control and quality assurance [9].

By taking over repetitive and physically demanding tasks, TLA lightens the physical and mental workload on staff. This shift gives them more time to focus on interpreting complex results and contributing meaningful clinical insights. Automation reduces direct contact with potentially infectious samples, which improves staff safety and helps create a healthier, more ergonomic, and supportive laboratory environment [1,10]. Quality assurance and error mitigation enhancements from total laboratory automation (TLA) standardisation across global institutions have yielded measurable improvements in diagnostic fidelity. Notable salient outcomes include attenuation of errors, automation of pre-analytical tasks such as sorting and aliquoting in a private diagnostic network, automated add-on protocols that obviate redraws, safeguarding of sample integrity and nullification of bio-risks [1,8].

Notwithstanding these advantages, the evidence is affected by contextual heterogeneity. Outcomes are predicated on variables including facility scale, assay diversity, and informatics interoperability, rendering universal extrapolation untenable. Implementation expenditures, encompassing capital outlay, training, and downtime, remain underexplored, posing fiscal risks for under-resourced entities. Moreover, while staff reallocation is efficacious, it necessitates proactive change management to avert attrition or morale erosion [11]. Despite their potential, challenges persist in feasibility (technical viability and integration), costing (initial investment, operational expenses, and return on investment), planning (strategic implementation and workflow optimisation), and designing (customisation, scalability, and safety considerations). Existing literature is fragmented, spanning engineering, health sciences, and management disciplines, with no comprehensive synthesis to guide stakeholders like researchers, policymakers, and industry professionals.

This study was carried out to study the extent and nature of the literature on the feasibility, costing, planning, and designing of automated robotic laboratory systems, to identify and map the key concepts, sources, and types of evidence related to

the topic, summarise findings on feasibility, costing, planning, and designing and highlight research gaps and recommend areas for future studies.

METHODOLOGY

This scoping review adheres to the Joanna Briggs Institute (JBI) methodology and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines. Eligibility criteria were defined using the Population/Concept/Context (PCC) framework, with inclusion encompassing laboratories in any sector as the population, automated robotic systems for laboratory processes as the concept, and feasibility, costing, planning, or designing aspects as the context. Sources included peer-reviewed articles and book chapters, with any study designs considered. Only English-language publications were included due to resource constraints. Only post-2015 sources were considered for relevance to modern robotics.

Exclusions comprised studies focused solely on non-laboratory robotics, opinion pieces without empirical data or structured analysis, duplicates or non-English sources, and irrelevant topics. Information sources consisted of electronic databases such as MEDLINE (via PubMed), Pubmed, and Embase. The search strategy was developed iteratively, incorporating preliminary keywords with an example PubMed string being ("automated"[tiab] OR "robotic"[tiab] OR "automation"[tiab]) AND ("laboratory"[tiab] OR "lab"[tiab]) AND ("feasibility"[tiab] OR "costing"[tiab] OR "planning"[tiab] OR "designing"[tiab]). Searches were documented, including dates, databases, and results. Study selection involved two reviewers independently screening titles and abstracts using Rayyan, with disagreements resolved by discussion or a third reviewer. The eligible abstracts proceeded to full-text assessment against criteria, and the selection process were reported via a PRISMA-ScR flow diagram as seen in **Figure 1**.

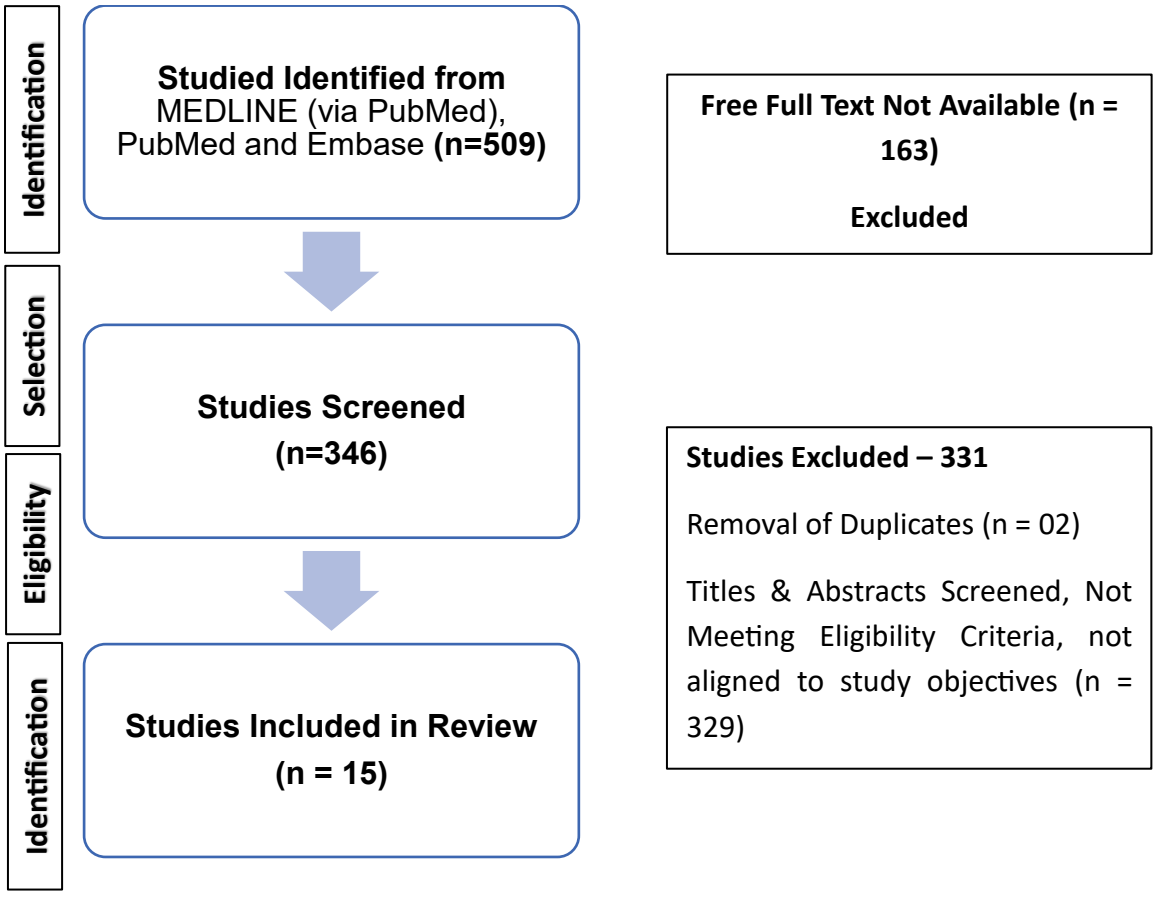

Figure 1 - PRISMA Flow Chart

RESULTS

The literature search yielded a total of 509 studies. After excluding 163 studies due to the unavailability of free full-text articles, 346 studies remained for title and abstract screening. Of these, 331 were excluded: 2 for duplication and 329 because their titles and abstracts did not meet the eligibility criteria or align with the study objectives. Consequently, 15 studies were included in the final review. These studies encompassed a range of designs, including qualitative case studies, quantitative evaluations, mixed-methods analyses, and reviews. The included sources originated from diverse sectors, such as clinical microbiology, pathology, chemistry, and general laboratory automation, with geographical representation from

India, North America, Europe, Asia, and international collaborations. The domain-wise results have been summarised in **Table 1**.

Table 1 - Domain-wise Key Findings of the Review

Aspect	Key Findings	References
Feasibility	Robotic track-based systems are feasible for high-volume biomedical labs. However, there are challenges in regulatory integration and in developing countries. TLA enhances Turn Around Time (e.g., urine from 73.7h to 40h).	Khare et al., 2023; Trigueiro et al., 2024 [12,13]
	TLA is feasible with AI/robotics/IoT. It addresses labour shortages but faces cybersecurity risks. Productivity from 49 to 110 samples/Full Time Equivalents/day.	Nam & Park, 2025; Trigueiro et al., 2024 [1,13]
	Feasible for small/medium labs should be done using decision trees. Repetitive processes are key. Lessons from other industries like task definition reduces human intervention.	Rupp et al., 2024, Zayas-Cabán et al., 2021 [14,15]
	Evolution to knowledge graphs/digital twins is feasible for drug discovery; mobile manipulators enable flexible Plug & Play.	Bai et al., 2022; Zsoldos et al., 2025 [16,17]
	Early 1990s vision feasible for standardisation and safety.	Godfery et al., 2020 [18]
	Feasible with digital tools and matrix complexity are addressed via liquid handlers/robots.	Munari et al., 2024; Thurow, 2023 [19,20]
Costing	Life Cycle Costing model over 10 years includes equipment, warranty, maintenance, and reagents; not just initial cost.	Khare et al., 2023 [12]
	High implementation but return on investments (ROI) via error minimisation/labour savings, lean unlocks further savings.	Nam & Park, 2025 [1]
	Savings from reduced skilled labour; reactivate unused equipment for ROI in Small and Medium Enterprises (SMEs).	Rupp et al., 2024 [14]
	Justified by declining reimbursement, knowledge graphs reduce labour/energy costs.	Ledeboers & Dallas, 2014; Bai et al., 2022 [16,21]
	Solid calculations in four labs show efficiency gains; ongoing monitoring ensures ROI.	Culbreath et al., 2021; Zayas-Cabán et al., 2021 [15,22]
	Laboratory Automation Plug & Play (LAPP) reduces integration costs; platforms replace costly manual hoods.	Godfery et al., 2020; Zsoldos et al., 2025 [17,18]
Planning	Two-bid system per regulations; financial analysis for strategic bids.	Khare et al., 2023 [12]
	Interdisciplinary planning required for Artificial Intelligence integration; advances needed for space/utilities/training.	Brunner, n.d; Nam & Park, 2025 [1,23]
	Decision aid prioritises processes; Lean Continuous Improvement Events enhance total laboratory automation.	Rupp et al., 2024; Trigueiro et al., 2024 [13,14]
	Task assessment from other industries; orchestrate the semantic web/multi-agents.	Bai et al., 2022; Zayas-Cabán et al., 2021 [15,16]
	Standardise chain-of-custody; select strategies based on complexity.	Munari et al., 2024; Thurow, 2023 [19,20]
	Ongoing monitoring post-total laboratory automation; integrate synthesis/analytical tools.	Culbreath et al., 2021; Godfrey et al., 2020 [10,18,22]
	SiLA/ROS for LAPP integration amid shortages.	Zsoldos et al., 2025; Ledeboers & Dallas, 2014

Aspect	Key Findings	References
		[17,21]
Designing	Track-based with robotics/AI; modular for scalability.	Khare et al., 2023; Nam & Park, 2025 [1,12]
	Custom for SMEs; digital pathology for secure storage.	Rupp et al., 2024; Munari et al., 2024 [14,19]
	Distributed with collaborative robots, knowledge graphs/digital twins.	Bai et al., 2022; Thurow, 2023 [16,20]
	BD Kiestra/Copan choices; fixed/flexible geometry.	Culbreath et al., 2021; Brunner, n.d [10,23]
	People/process/tech balance; lean for transport/reading.	Trigueiro et al., 2024; Zayas-Cabán et al., 2021 [13,15]
	Platforms like ChemPuter with Machine Learning, mobile manipulators for Plug & Play.	Godfrey et al., 2020; Zsoldos et al., 2025 [17,18]
	Mass spec/robotics for standardisation.	Ledeboers & Dallas, 2014 [21]
Technical Specifications	Track-based robotics for high-volume, 10-year hardware lifecycle with modular integration.	Khare et al., 2023 [12]
	AI/ML/Robotics/IoT; modular tracks for predictive analytics and automated phases.	Nam & Park, 2025 [24]
	Liquid handlers with bioanalytical software; scalable for repetitive tasks in SMEs.	Rupp et al., 2024 [14,19]
	Digital pathology: Controlled storage, AI image analysis, traceable labelling.	Munari et al., 2024 [19]
	Liquid handlers/central/collaborative robots; user-programmable for distributed systems.	Thurow, 2023 [20]
	BD Kiestra/Copan: Inoculation, transportation, smart incubators with digital reading; instrument connectivity.	Culbreath et al., 2021 [22]
	Knowledge graphs/digital twins: ML algorithms, semantic web, multi-agent systems for synthesis.	Bai et at., 2022 [16]
	Low/full automation: Robotics with APF/gradient methods for task streamlining.	Zayas-Cabán et al., 2021 [15]
	WASPLab/VITEK MS: Plate handling, digital imaging; lean-integrated.	Trigueiro et al., 2024 [13]
	SynCAR/ASL/ChemKonzert/ChemPuter: Automated synthesis (peptides/boronates); flow chemistry; high-throughput screening.	Godfrey et al., 2020 [18]
	Automated plating, mass spec, liquid media; microbial detection, nucleic acid amp, ID/AST, digital imaging.	Ledeboer & Dallas, 2014 [21]
	TIAGo manipulator: SiLA/ROS frameworks; labware transfer, digital twins.	Zsoldos et al., 2025 [17]

DISCUSSION

This scoping review synthesises the available evidence on the feasibility, costing, planning, designing, and technical specifications of automated robotic laboratory systems, drawing from diverse sources spanning clinical microbiology, pathology, chemistry, and broader automation trends. The findings underscore the transformative potential of these systems in enhancing laboratory efficiency, accuracy, and throughput, particularly in high-volume settings where TLA integrates robotics, Artificial Intelligence, and Internet of Things to address labour shortages and reduce Turnaround Time (TAT). However, challenges such as high initial implementation costs, regulatory integration in developing contexts, and the need for scalable, interoperable designs highlight the importance of strategic planning and life cycle costing to maximise Return on Investment (ROI). By examining these dimensions, this discussion explores the implications for laboratory stakeholders,

identifies evidence gaps, and proposes directions for future research to advance adoption and innovation in automated systems.

Findings from the studies carried out by Khare et al. (2023) and Trigueiro et al. (2024) indicate that robotic systems using track-based mechanisms are practical and viable in laboratories handling large numbers of samples, such as those in biomedical research or clinical settings. They incorporate track-based systems, which are conveyors for samples with robotics and use Artificial Intelligence for intelligence. Modularity, which ensures interchangeable components, allows scalability, suiting the needs of a growing laboratory. However, challenges arise in integrating them with regulatory requirements, especially in developing countries, where infrastructure, funding, or expertise may be limited. The designs are customised for Small and Medium Enterprises (SMEs) to fit budgets [12,13].

Nam & Park (2025) and Trigueiro et al. (2024) reported that the TLA is viable when combined with Artificial Intelligence, Robotics, and Internet of Things, e.g., sensors monitoring lab conditions. This integration makes TLA feasible by automating workflows, thus solving issues like labour shortages. For instance, productivity can increase from 49 samples processed per Full-Time Equivalent per day to 110, meaning labs can handle more work with the same staff. However, cybersecurity risks pose challenges, requiring secure protocols. This finding underscores TLA's role in modern labs for efficiency but highlights the need for risk management [1,13].

Rupp et al. (2023) and Zayas-Cabán et al. (2021) found that Automation is practical in Small and Medium Enterprises using decision trees. Repetitive processes (e.g., routine sample pipetting) are ideal candidates, as they benefit most from standardisation and error reduction. Drawing lessons from industries like finance or manufacturing, clearly defining tasks (e.g., breaking them into steps like "transport sample" or "analyse data") minimises human intervention, making automation more efficient and safer. This is important for smaller labs, where full-scale systems might be overkill, but targeted automation can still improve throughput without overwhelming resources [14,15,21].

Bai et al. (2022) and Zsoldos et al. (2025) in their studies report that the progression from basic automation platforms to advanced knowledge graphs and digital twins is viable for drug discovery. This evolution allows for autonomous experimentation. Mobile manipulators support flexible Laboratory Automation Plug & Play, making systems adaptable. This feasibility is key for innovative fields, as it bridges virtual planning and real-world execution, but it requires mature hardware/software.

Ledeboer & Dallas (2014) argue that automation in microbiology is an ongoing, realistic process rather than an unattainable "fantasy." It significantly reduces Turnaround Time (TAT), for example, shortening urine sample analysis from days to 16–20 hours by automating steps like plate reading. This addresses real-world issues like workforce shortages, making it feasible for routine diagnostics. The finding emphasises that while benefits are clear, continuous improvements are needed to sustain them.[21].

Visions from the 1990s for full lab automation are now feasible, particularly for standardising procedures and enhancing[23]. Godfrey et al. (2020) report that this perspective shows automation's long-term viability, evolving from basic tools to integrated systems. In chemistry labs, platforms like SynCAR replace traditional benches, automating tasks like peptide synthesis [18].

Studies of Munari et al. (2023) and Thurow (2023) in pathology state that automation is viable using digital tools. Complex matrices like sample compositions and varied biological fluids are managed with liquid handlers and robots, improving traceability and efficiency. This feasibility is crucial for diagnostic accuracy, as it standardises handling and reduces manual errors [19,20].

Khare et al. (2023) report that Life Cycle Costing is a method to evaluate total costs over an asset's lifespan. It factors in not only the upfront purchase price but also ongoing expenses like warranties, maintenance, and consumables. This holistic approach ensures better decision-making, as focusing solely on initial costs can lead to underestimating long-term expenses, making it essential for budgeting in resource-limited settings. They reported that planning follows a two-bid system, i.e. separate technical and price evaluations as per regulations, e.g., General Finance Rules or GFR 2017 in India. This includes financial analysis by assessing costs/benefits for strategic bidding, ensuring selections are value driven. It's crucial for transparent procurement [12]. Automation requires significant upfront investment, but it yields a return on Investment through reduced errors and labour savings. Lean principles like Continuous Improvement Events further enhance savings by optimising workflows. This is vital for justifying automation in clinical labs, as stated by Nam & Park (2025) and Trigueiro et al. (2024) [1,13].

Rupp et al. (2023) found that cost benefits arise from needing fewer highly skilled workers as automation handles repetitive tasks, leading to labour savings. In Small and Medium Enterprises (SMEs), reactivating idle equipment can accelerate Return on Investment without new purchases. This practical approach makes automation affordable for smaller operations [14].

Ledeboer & Dallas (2014) and Bai et al. (2022) found that automation is cost-justified amid declining reimbursement. Knowledge graphs streamline processes, cutting labour and energy costs. This supports sustainability in labs facing financial pressures. Detailed financial analyses in four different-sized labs demonstrate efficiency improvements like faster processing, leading to cost savings. Ongoing monitoring, which includes regular checks on performance, is key to sustaining Return on Investment (ROI), preventing issues like downtime. This evidence-based finding validates automation's economic value as per Zayas-Cabán et al. (2021) [15,16,21].

Zsoldos et al. (2025) and Godfrey et al. (2020) found that Laboratory Automation Plug & Play (LAPP) simplifies device connections, lowering integration costs. Platforms replace expensive manual fume hoods, reducing operational expenses. This makes automation more accessible.

As per Nam & Park (2025) and Brunner (1990s), planning requires interdisciplinary collaboration, e.g., engineers and clinicians, for Artificial Intelligence integration. Advance preparation covers space (lab layout), utilities (power/water), and training (staff skills), preventing implementation delays [23,24]. Rupp et al. (2023) and Trigueiro et al. (2024) recommend using a decision aid tool like a flowchart or a decision tree, which helps prioritise processes for automation. Lean principles, via Continuous Improvement Events (CIE), structured workshops for optimisation, boost Total Laboratory Automation (TLA) by refining workflows [14]. This strategic planning maximises benefits. Planning also involves assessing tasks, e.g., defining steps using lessons from industries like manufacturing. Orchestrating the semantic web and multi-agent systems, ensuring seamless integration for complex automation as per Zayas-Cabán et al. (2021) and Bai et al. (2022) [15,16].

As per Munari et al. (2023) and Thurow (2023), planning standardises the chain-of-custody, like tracking samples from collection to storage for security. Strategies are selected based on process complexity, optimising implementation [19,20]. Godfrey et al. (2020) recommend that post-implementation planning include ongoing monitoring of performance checks after Total Laboratory Automation (TLA) [17,18,21]. Integrating synthesis and analytical tools ensures holistic workflows. Zsoldos et al. (2025) and Ledeboer & Dallas (2014) reported that planning uses Standardisation in Laboratory Instrumentation and Robot Operating System for Laboratory Automation Plug & Play (LAPP) integration. This addresses workforce shortages by enabling efficient setups [17,21].

Digital pathology ensures secure storage and enhances data integrity as reported by Rupp et al. (2023) and Munari et al. (2023) [14,19]. Distributed designs that have spread-out systems use collaborative robots that work safely with humans. Knowledge graphs and digital twins enable simulation and optimisation as per Thurow (2023) and Bai et al. (2022) [16,20]. Zayas-Cabán et al. (2021) and Trigueiro et al. (2024) inferred that designs balance people (human roles), processes (workflows), and technology. Lean principles optimise transport and analysis [13,15].

The technical specifications identified in this scoping review reveal a diverse and evolving landscape of automated robotic laboratory systems, characterised by modular hardware, advanced software integration, and capabilities tailored to high-throughput and complex workflows. Track-based robotics, as exemplified in high-volume biomedical applications, supports a 10-year hardware lifecycle with modular integration for seamless scalability.

Advanced systems incorporate Artificial Intelligence, Machine Learning, robotics, and Internet of Things technologies, enabling predictive analytics and automation across pre-analytical, analytical, and post-analytical phases through modular tracks. Liquid handlers paired with bioanalytical software are scalable for repetitive tasks in Small and Medium Enterprises, while digital pathology systems feature controlled storage environments, AI-driven image analysis, and traceable labelling to enhance diagnostic accuracy and sample security. Distributed designs leverage liquid handlers, central robots, and collaborative robots with user-programmable interfaces for flexible, networked operations.

CONCLUSION

This scoping review maps the current landscape of evidence on the feasibility, costing, planning, and designing of automated robotic laboratory systems, with particular emphasis on total laboratory automation (TLA). It consistently demonstrates substantial operational gains. These include TAT reductions, increased throughput capacity, meaningful staff reallocation from repetitive tasks, and enhanced quality assurance through error mitigation and higher auto-validation rates. By integrating robotics, AI, and informatics across pre-analytical, analytical, and post-analytical phases, these systems not only boost efficiency and diagnostic reliability but also improve workplace safety and ergonomics by reducing physical and cognitive burdens on laboratory personnel.

Critical gaps persist in low-income and middle-income country contexts, paediatric or low-volume settings, and emerging technologies such as collaborative robots and fully autonomous “self-driving” labs. Future research should prioritise multi-centre prospective studies, health-economic evaluations incorporating indirect benefits, and standardised planning toolkits to support equitable adoption. As healthcare systems face escalating diagnostic demands, strategic investment in thoughtfully designed robotic automation holds transformative potential to create more sustainable, safer, and patient-centred laboratory environments worldwide.

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