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ARTIFICIAL INTELLIGENCE IN CLINICAL LABORATORIES: A BIBLIOMETRIC ANALYSIS OF RESEARCH TRENDS AND APPLICATIONS

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ABSTRACT
The progress of artificial intelligence (AI) has rapidly increased its use in clinical laboratories, making it easier to diagnose patients and run the laboratories more efficiently. Nonetheless, difficulties remain regarding the ethical aspects, uniformity, and reliability of algorithmic decision-making. This study seeks to delineate the evolution of AI applications in clinical laboratories over the preceding five years through a bibliometric analysis. We obtained original articles from the Scopus database published between 2021 and 2025 in the fields of medicine, computer science, and health professions. A systematic identification and screening process resulted in 1,891 documents, followed by filtering, duplicate removal, and eligibility assessment, giving in the inclusion of 994 studies in the final analysis. We conducted a bibliometric analysis to examine publication trends, changes in themes over time, co-occurrence of keywords, networks of international collaboration, and highly cited core studies. The results show that research output is growing quickly, and the focus is shifting from developing new methods to putting them into practice in the real world. Keyword mapping indicates that automation, diagnostic accuracy, and decision-support systems are becoming increasingly important. International collaboration is growing, but it is still unevenly distributed across regions. In conclusion, this study offers a thorough examination of the evolving research landscape of AI in clinical laboratories and underscores the need for enhanced global collaboration and the ethical, clinically reliable, and sustainable incorporation of AI in clinical laboratories.

Keywords: artificial intelligence; bibliometric analysis; clinical laboratory

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INTRODUCTION

The growth of artificial intelligence (AI) has changed many parts of healthcare, such as clinical laboratory operations, by making diagnostics more accurate, operations more efficient, and data management more real-time. AI makes it possible to automate analytical processes in laboratory medicine, from auto-validation and interpretation of laboratory and histopathological results to predicting test outcomes. AI also helps doctors make decisions based on data (Elechi et al., 2025). These features are even better when they are linked to laboratory automation systems. This makes workflows smoother, lowers the number of mistakes, and improves overall performance (Giesriegl et al., 2025). At the same time, the growing use of big data and predictive analytics allows AI to support risk stratification and uncover clinically meaningful patterns within complex datasets (Krittanawong et al., 2017).

Despite these advances, the adoption of AI in clinical laboratories remains constrained by unresolved technical, ethical, and infrastructural challenges, many of which vary substantially across settings. Concerns related to algorithmic bias, limited interpretability, and data privacy continue to affect the reliability and trustworthiness of AI systems (Aradhya et al., 2023; Xie et al., 2024). In practice, successful implementation necessitates extensive, high-quality datasets and significant computational resources, while data heterogeneity and the absence of standardization exacerbate integration challenges across systems (van Diest et al., 2024). It is important to note that making AI a part of everyday clinical workflows is not easy. It requires interoperability, regulatory alignment, and strong data governance frameworks (Hou et al., 2024; Krittanawong et al., 2017). In this context, unresolved ethical considerations and the absence of consistent regulatory standards remain key obstacles to broader adoption (Ehrenfeld & Woeltje, 2024).

Despite these limitations, AI applications in clinical laboratories have continued to expand. Current use cases include instrument error detection, workflow optimization, and large-scale data analysis for disease prediction and patient risk stratification. Several studies have reported improvements in diagnostic turnaround time and workload reduction (Ashraf et al., 2025), as well as in the accuracy and efficiency of analysis (Berkhout et al., 2025; Lukman & Atoe, 2025). However, putting it into practice in the real world is still hard because it doesn't work well with old laboratory information systems and requires a lot of money to build new infrastructure. As highlighted in clinical implementation studies, successful integration depends not only on technical capability but also on workflow redesign, stakeholder engagement, and continuous system validation (Sendak et al., 2020).

Given this evolving yet fragmented landscape, a broader understanding of how research in this field has developed is still lacking. Although the volume of studies on AI in clinical laboratories has increased in recent years, existing literature tends to focus on specific applications or technical performance, with limited attention to the overall research trajectory. In particular, insights into publication trends, thematic evolution, collaborative networks, and influential contributions remain insufficient. To address this gap, this study aims to examine the development of AI research in clinical laboratories over the past five years using a bibliometric approach. By analyzing publication patterns, research themes, and international collaborations, this study seeks to provide a more comprehensive overview of the field and to identify potential directions for future research.

METHOD

This study adopted a bibliometric design to analyse scientific publications indexed in the Scopus database. Data retrieval was conducted using a structured keyword-based search strategy to ensure comprehensive coverage and high data reliability.

The primary search query was:
TITLE-ABS-KEY (("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("clinical laboratory" OR "medical laboratory" OR "hospital laboratory" OR "pathology lab"))

To capture studies focusing on real-world implementation, a complementary query was applied:
(("AI application" OR "AI implementation") AND "hospital")
Records obtained from both searches were merged, and duplicate entries were removed prior to analysis.

Inclusion criteria comprised journal articles published between 2021 and 2025, written in English, and indexed under the subject areas of Medicine, Computer Science, and Health Professions. Only documents classified as “Article” were included to ensure peer-reviewed scientific quality.

The final dataset was exported in BibTeX format and analysed using the Biblioshiny web interface of the Bibliometrix package (RStudio). Bibliometric indicators and network analyses were performed to evaluate publication trends, collaboration patterns, keyword co-occurrence, thematic evolution, and co-citation structures.

RESULT

Study Selection and Dataset Characteristics

The literature search yielded a total of 1,891 records, including 1,435 articles retrieved using the keywords related to "AI and healthcare" and 396 articles related to "AI and hospital." After applying inclusion criteria, subject area filters, time restrictions, and removing duplicate records, 994 articles were retained for bibliometric analysis (Figure 1).

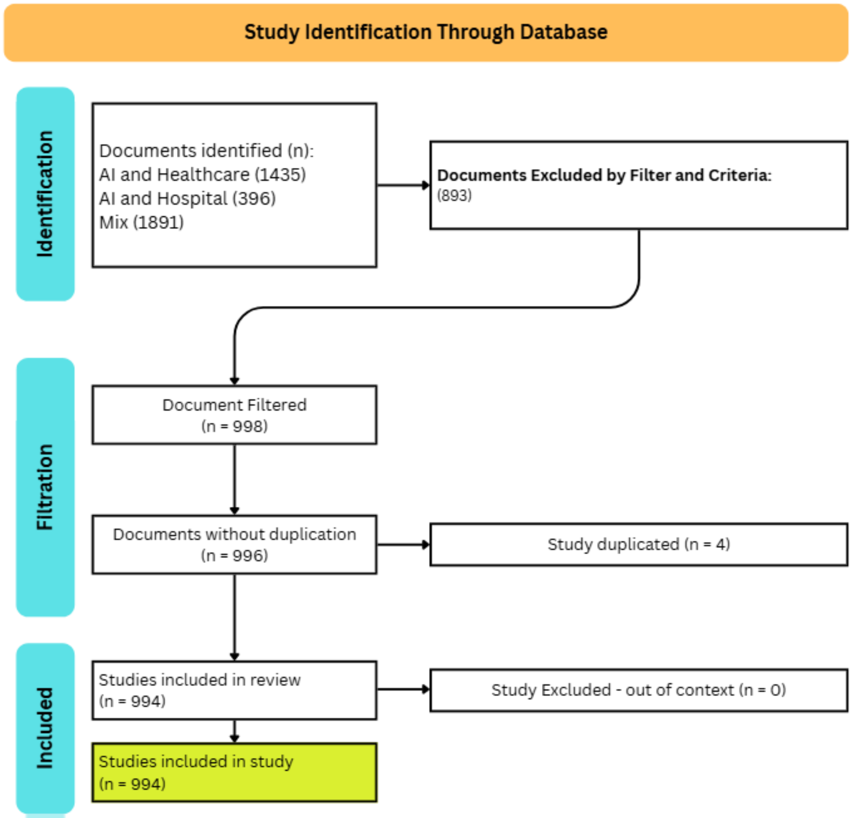

Figure 1. Flowchart of study identification, screening, and inclusion process for the bibliometric analysis.

This bibliometric analysis covers the period from 2021 to 2025 and includes 974 documents published in 504 sources, involving a total of 6,191 authors. Only 54 documents were single-authored, indicating that research in this field is predominantly collaborative. This is further supported by the high average number of co-authors per document (7.39) and a moderate level of international collaboration, with 23.51% of publications involving authors from multiple countries. Moreover, in terms of thematic and temporal characteristics, the dataset contains 2,675 author keywords, reflecting considerable diversity in research topics. The average document age was 2.45 years, suggesting that the literature is relatively recent and dynamically evolving. The mean citation rate reached 12.15 citations per document, indicating a moderate scholarly impact. Notably, the annual publication growth rate was positive at 33.12%, demonstrating a substantial increase in research output during the analysed period and highlighting the growing academic interest in this field (Figure 2).

Figure 2. Bibliometric overview of publication output, authorship patterns, collaboration metrics, and citation characteristics (2021–2025).

Publication Growth and Journal Productivity

The maturity trend analysis (Figure 3) indicates that research on AI in clinical laboratories is currently in an early growth stage. The fitted logistic model demonstrates good performance (R^2 = 0.962), suggesting that the observed publication trajectory is adequately captured by the model. As of 2025, the cumulative number of publications reached 974, representing approximately 10% of the estimated saturation level (K ≈ 9,740), with an annual output of 336 articles.

Model projections suggest that publication activity may continue to increase over the next decade, with the midpoint of growth expected around 2031 and a projected peak annual output of approximately 842 publications. Forecasts estimate cumulative publications of about 3,918 by 2030 and 7,708 by 2035. These findings indicate sustained expansion of the field, although the topic has not yet reached maturity and remains in a phase of rapid development (Figure 3).

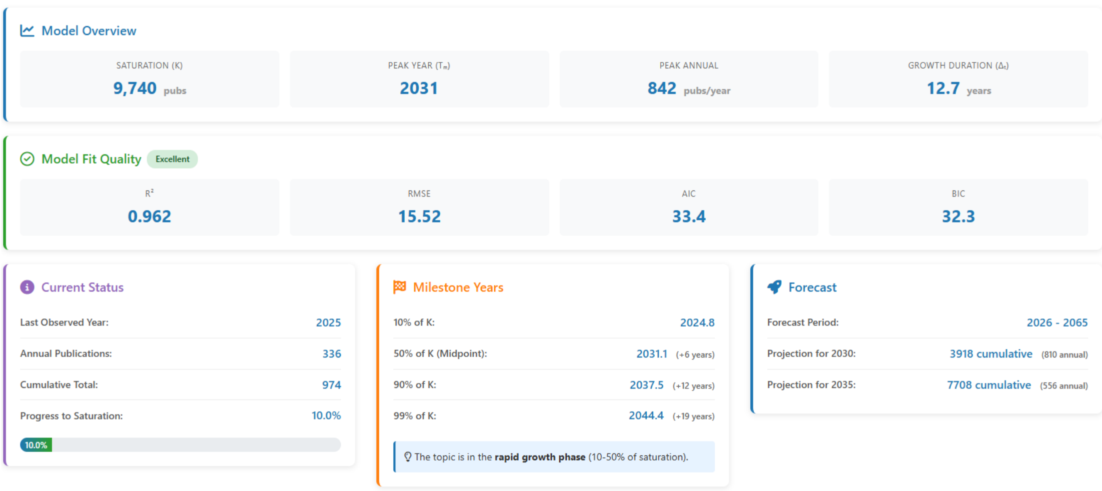

Figure 3. Maturity trend analysis of AI research in clinical laboratories

The annual scientific production (Figure 4) shows a steady increase from 2021 to 2025, with the number of publications rising from approximately 105 articles in 2021 to a peak of 336 articles in 2025. This pattern indicates a gradual intensification of research activity over the observed period, particularly after 2023, when the growth rate became more pronounced.

In contrast, a marked decline is observed in 2026 (Figure 4), with a substantially lower number of publications recorded. This decrease is likely attributable to partial-year data coverage or indexing delays rather than a definitive reduction in research output. The fitted linear trendline demonstrates a weak explanatory power (R^2 = 0.0094), suggesting that short-term fluctuations and structural changes may not be adequately captured by a simple linear model.

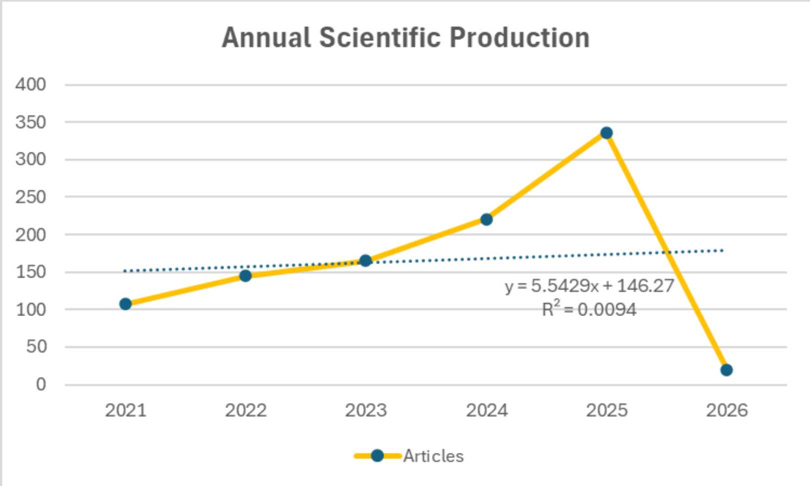

Figure 4. Annual scientific production.

Journal productivity demonstrated a marked shift toward discipline-specific outlets. *Clinical Chemistry and Laboratory Medicine* and *Clinical Chemistry* emerged as the most productive journals, showing steady growth between 2021 and 2025. In contrast, journals such as *Digital Health* and the *Chinese Journal of Laboratory Medicine* began contributing more substantially after 2023, indicating increasing regional and applied research engagement (Table 1).

Table 1.
Annual publication output of the most productive journals in artificial intelligence research within clinical laboratory medicine (2021–2026)

Year	Clinical Chemistry and Laboratory Medicine	Clinical Chemistry	Journal of Medical Internet Research	Chinese Journal of Laboratory Medicine	Digital Health	Journal of Clinical Medicine
2021	2	2	5	0	0	1
2022	10	6	6	2	0	3
2023	18	13	6	2	0	8
2024	29	19	7	4	5	9
2025	42	22	13	10	10	10
2026	45	22	13	10	10	10

Authorship Pattern and Lotka's Law

Lotka's Law analysis (Table 2) revealed that 91.6% of authors contributed only one publication, significantly exceeding the theoretical expectation of 63.3%. Less than 1% of authors published more than five articles. This pattern suggests that AI research in clinical laboratories remains highly multidisciplinary and exploratory, with limited consolidation among core research groups.

Table 2.
Author productivity distribution based on Lotka's law.

Documents written	N. of Authors	Proportion of Authors	Theoretical
1	5743	0.916	0.633
2	338	0.054	0.158
3	86	0.014	0.07
4	42	0.007	0.04
5	26	0.004	0.025
6	7	0.001	0.018
7	9	0.001	0.013
8	3	0	0.01
9	7	0.001	0.008
10	4	0.001	0.006

Keyword Analysis and Research Themes

Keyword frequency analysis demonstrated a shift from predominantly technological terminology toward clinically oriented research. The most frequent keywords included *human*, *artificial intelligence*, and *machine learning*, followed by demographic descriptors such as *female*, *male*, and *adult*, reflecting increased emphasis on patient-centered clinical validation (Table 3).

Table 3.
Top 10 most frequent keywords in the analyzed publications.

Words	Occurrences
human	703
artificial intelligence	492
article	476
humans	465
machine learning	465
female	311
male	292
adult	270
clinical laboratory	251
controlled study	241

The word cloud visualization (Figure 5) highlights the dominant research themes in the analyzed literature, with strong emphasis on *artificial intelligence*, *machine learning*, *diagnosis*, and *clinical laboratory*. The frequent occurrence of terms such as *deep learning*, *sensitivity and specificity*, *controlled study*, and *diagnostic accuracy* indicates that current research extends beyond algorithm development toward systematic performance evaluation and clinical validation.

Notably, the prominence of diagnostic performance metrics reflects an increasing focus on clinical reliability, regulatory acceptance, and translational applicability of AI-based systems. Furthermore, the recurrent appearance of *clinical laboratory* as a central keyword suggests a growing integration of AI technologies into routine laboratory workflows rather than isolated experimental or pilot settings.

Overall, these patterns indicate a gradual shift in the literature from proof-of-concept studies toward outcome-oriented research that prioritizes diagnostic utility, methodological robustness, reproducibility, and patient-centered clinical relevance.

Figure 5. Word cloud of the most frequent keywords in the analyzed publications, where larger fonts indicate higher frequency. Dominant terms (*human(s)*, *artificial intelligence*, *machine learning*) highlight the focus on AI-driven clinical and laboratory research.

The co-occurrence network in Figure 6 reveals three dominant thematic clusters. The red cluster centers on the linkage between *human/humans* and core AI-related terms such as *artificial intelligence* and *machine learning*, alongside the contextual term *clinical laboratory*, suggesting a strong emphasis on the technical integration of AI within clinical laboratory practice. The blue cluster highlights methodological and demographic dimensions, connecting *article* to population descriptors (*female*, *male*, *adult*) and study designs such as *controlled study* and *major clinical study*, indicating that a substantial portion of the literature focuses on clinically oriented evaluation frameworks. A smaller green cluster is driven by *COVID-19*–related terms, implying that the pandemic served as a catalyst for accelerated AI adoption and research activity in hospital/clinical laboratory settings.

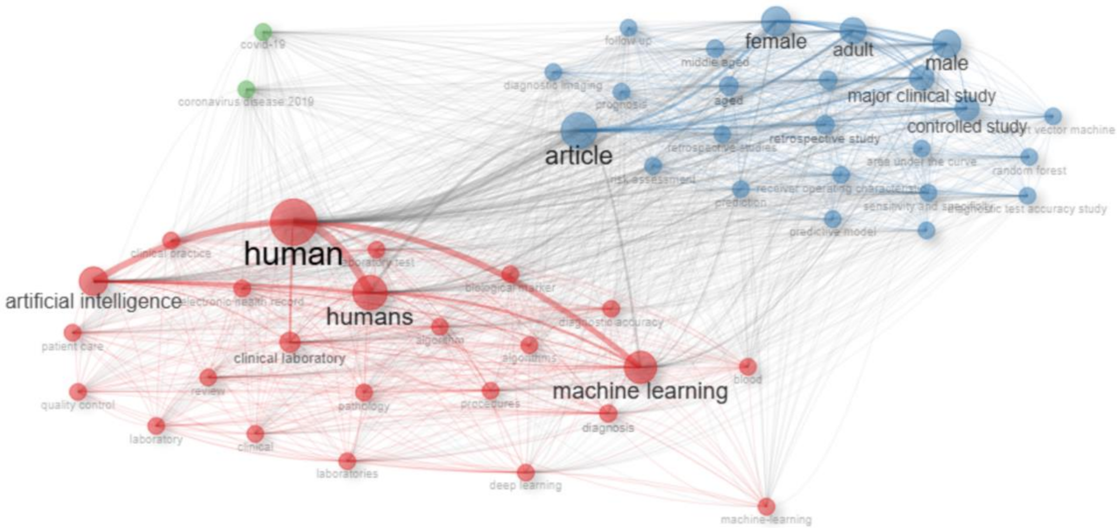

Figure 6. Keyword co-occurrence network showing major thematic clusters in the analyzed publications, with strong linkages between *human(s)*, *machine learning*, and *artificial intelligence*, indicating close integration of AI methods in human-centered clinical research

The factorial analysis using Multiple Correspondence Analysis (MCA) provides deeper insight into the conceptual structure of AI research in clinical laboratories by mapping the proximity of keywords across two principal dimensions (Figure 6). Dimension 1, accounting for 82.44% of the total variance, represents the primary intellectual axis of the field and clearly separates observational and descriptive research on the left from clinically oriented implementation studies on the right. Keywords located on the left side, such as *retrospective study*, *controlled study*, and *clinical studies*, reflect earlier research stages that primarily focused on methodological validation, data exploration, and performance assessment under controlled conditions. In contrast, the right side of the plot is dominated by application-oriented terms, including *clinical*, *laboratories*, *workflow*, *patient care*, *clinical practice*, and *electronic health record*, indicating a strong shift toward operational integration of AI into routine laboratory services and clinical decision-making processes. The upper-right quadrant, in particular, highlights a convergence between laboratory workflow optimization and patient-centered care, suggesting that recent studies increasingly frame AI not merely as a diagnostic tool but as a system-level intervention aimed at improving efficiency, reducing turnaround time, and enhancing the quality of clinical services. This pattern reflects the maturation of the field toward translational and implementation-driven research. Meanwhile, technical terms such as *deep learning* and *machine learning* appear in the lower region of the map, positioned closer to the origin. This spatial distribution implies that these technologies function as foundational enablers rather than dominant conceptual drivers, supporting higher-level clinical objectives rather than defining the research agenda themselves. The presence of *COVID-19* near the center further indicates its transitional role in bridging methodological development and large-scale clinical deployment during the pandemic period. Overall, the MCA results demonstrate a conceptual evolution from technology-centered experimentation toward clinically integrated, outcome-oriented research, reinforcing the interpretation that AI in clinical laboratories is progressing from algorithm development to practical, patient-impacting applications.

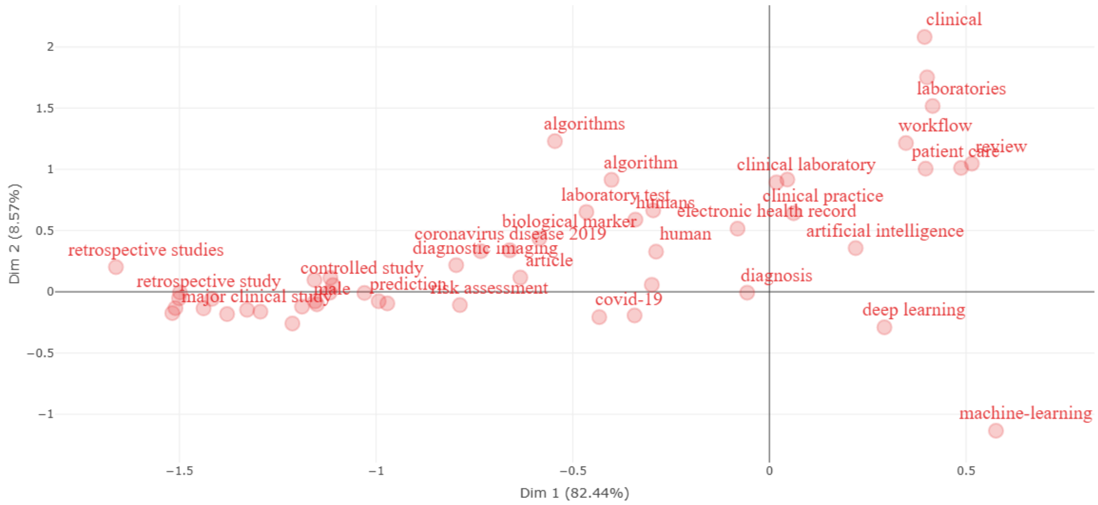

Figure 7. Conceptual structure map of keywords based on multiple correspondence analysis (MCA), illustrating the relationships and clustering of major research themes in artificial intelligence–based clinical laboratory studies

International Collaboration Patterns

The global collaboration map in Figure 8 illustrates that research on artificial intelligence in clinical laboratories is predominantly driven by high-income countries and several major emerging economies. The United States and China appear as the most prominent global collaboration hubs, indicated by the darkest red color intensity and the highest density of international linkages. These two countries serve as central nodes connecting multiple regions, reflecting their leading roles in AI development and biomedical research capacity.

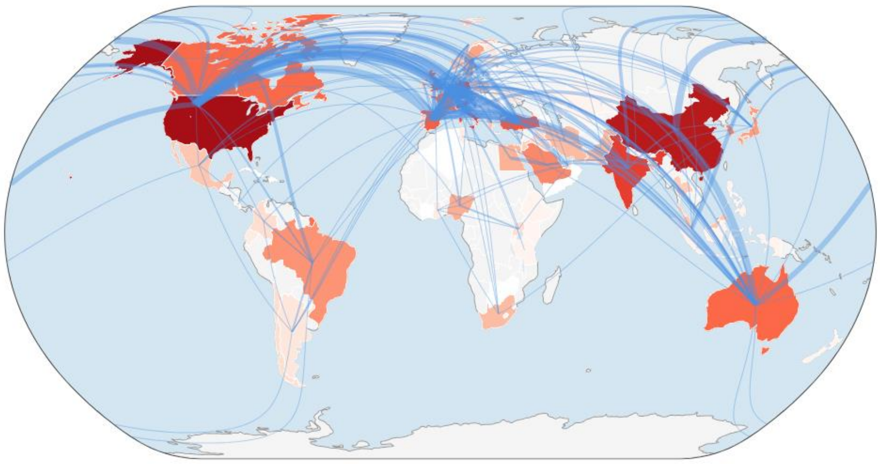

Figure 8. Global map of international research collaboration, illustrating cross-country co-authorship links and the geographic distribution of collaborative networks in AI-based clinical and laboratory studies**.**

Other notable contributors include India, Australia, and several European countries, which form secondary collaboration centers and maintain strong bilateral and multilateral research partnerships. The dense network of connecting lines demonstrates robust cross-continental cooperation, particularly between North America, Europe, and East Asia. In contrast, contributions from Africa and parts of Southeast Asia and Latin America remain comparatively limited, highlighting persistent geographical disparities in research infrastructure and funding capacity.

Overall, this spatial distribution confirms that AI research in clinical laboratories is shaped by globally interconnected but unevenly distributed scientific networks. The observed collaboration pattern is consistent with the international co-authorship rate of 23.54% identified in this study, indicating a moderate yet structurally significant level of cross-border research integration within the field.

Evolution of Research Topics

The topic trend analysis presented in Table 4 reveals a clear and dynamic evolution of research focus on artificial intelligence in clinical laboratories over the past five years, which can be broadly divided into three developmental phases.

Table 4.
Evolution of Major Research Topics

Term	Frequency	Year (Q1)	Year (Median)	Year (Q3)
priority journal	14	2021	2021	2021
fever	9	2021	2021	2024
virology	8	2021	2021	2024
covid-19	73	2021	2022	2024
coronavirus disease 2019	63	2021	2022	2024
sars-cov-2	40	2021	2022	2022
deep learning	160	2022	2023	2025
laboratories	115	2022	2023	2025
retrospective studies	82	2022	2023	2025
human	703	2022	2024	2025
artificial intelligence	492	2023	2024	2025
article	476	2022	2024	2025
diagnosis	208	2023	2025	2025
middle aged	139	2023	2025	2025
predictive model	77	2023	2025	2025

Phase 1: Pandemic-Driven Research (2021–2022).

During the early period, research was predominantly shaped by the urgent global health crisis caused by COVID-19. This phase is characterized by the frequent occurrence of terms such as *priority journal*, *virology*, and *fever*, which peaked in 2021, reflecting rapid scientific dissemination and emergency-oriented investigations. Pandemic-specific keywords including *COVID-19* (frequency = 73), *coronavirus disease 2019* (63), and *SARS-CoV-2* (40) exhibited median publication years in 2022, indicating sustained research activity focused on diagnostic support, viral detection, and laboratory-based surveillance systems using AI technologies.

Phase 2: Transition toward Technical and Methodological Consolidation (2022–2023).

From 2022 onward, the research agenda shifted toward strengthening technical foundations and laboratory infrastructure. Keywords such as *deep learning* (160) and *laboratories* (115), both with a median year of 2023, highlight growing interest in advanced algorithmic architectures and their operational deployment within laboratory environments. Concurrently, the rising prominence of *retrospective studies* (82) indicates a methodological transition toward evaluating real-world system performance using historical datasets, signaling a move from experimental development to evidence-based validation of AI tools.

Phase 3: Clinical Maturity and Patient-Centered Application (2024–2025).

In the most recent phase, research attention has increasingly converged on clinical applicability and human-centered outcomes. The terms *human* (703) and *artificial intelligence* (492) reached median publication years in 2024, reflecting intensified integration of AI into patient-related diagnostic processes. By 2025, thematic emphasis expanded to *diagnosis* (208), *predictive model* (77), and demographic descriptors such as *middle aged*, suggesting a maturation of the field toward precision diagnostics and risk stratification. This phase indicates that AI research has progressed beyond technological feasibility toward standardized predictive modeling aimed at supporting clinical decision-making and personalized patient management.

Overall, these temporal patterns demonstrate a progressive transformation of the field, from crisis-responsive innovation, through technical consolidation, to clinically oriented implementation, highlighting the increasing role of AI as a core component of modern laboratory medicine.

Highly Cited Representative Studies

The highly cited representative studies listed in Table 5 were selected based on the highest total citation counts, reflecting their scientific impact and influence in shaping research directions on artificial intelligence in clinical laboratories.

Overall, these studies demonstrate that highly influential research in this field predominantly focuses on the integration of AI with clinical data, advanced machine learning techniques, and real-world diagnostic applications. The citation patterns indicate strong scholarly attention to personalized laboratory prediction, pandemic-related diagnostic support, explainable AI models, multimodal data analysis, and automated disease detection.

Collectively, the prominence of these topics suggests that impactful research has progressively shifted from experimental algorithm development toward clinically relevant implementation, emphasizing diagnostic accuracy, interpretability, and decision-support systems. This trend highlights the maturation of AI from a technical innovation into a core component of modern laboratory medicine and patient-centered healthcare delivery.

Table 5.
The most representative and highly cited studies on artificial intelligence applications in clinical laboratory settings, ranked by total citations and citations per year

Author(s)	Publication year	Article Title	Total Citations	Citations per year
Li X	2021	Wearable Sensors Enable Personalized Predictions Of Clinical Laboratory Measurements	183	30.5
Wang L	2021	Artificial Intelligence For Covid-19: A Systematic Review	134	22.333
Wang J	2021	A Deep Learning Based Framework For Diagnosing Multiple Skin Diseases In A Clinical Environment	78	13
Wang L	2022	Identification Of Bacterial Pathogens At Genus And Species Levels Through Combination Of Raman Spectrometry And Deep-Learning Algorithms	46	9.2
Wang Y	2023	An Improved Explainable Artificial Intelligence Tool In Healthcare For Hospital Recommendation	45	11.25
Wang J	2022	Clinlabomics: Leveraging Clinical Laboratory Data By Data Mining Strategies	37	7.4
Wang Y	2022	Radiomics Analysis Allows For Precise Prediction Of Silent Corticotroph Adenoma Among Non-Functioning Pituitary Adenomas	35	7

DISCUSSION

The findings position artificial intelligence research in clinical laboratories within an early yet rapidly expanding growth phase. An annual growth rate of 33% and attainment of only approximately 10% of the projected saturation level indicate that the field remains far from maturity, reflecting continued expansion rather than stabilization. This trajectory is consistent with broader bibliometric evidence demonstrating exponential growth of AI research in healthcare, driven by increasing scientific and clinical interest (Senthil et al., 2024). The growing dominance of discipline-specific journals such as Clinical Chemistry and Laboratory Medicine and Clinical Chemistry further suggests emerging consolidation within core laboratory medicine domains. This pattern reflects a transition from broad exploratory activity toward more structured disciplinary integration, supported by the expanding role of AI across pre-analytical, analytical, and post-analytical phases, as well as its increasing application in predictive analytics, diagnostic decision support, and integration with clinical data infrastructures such as electronic health records (Md Habibur et al., 2025).

Authorship and collaboration patterns indicate a fragmented yet highly multidisciplinary research landscape. The predominance of single-publication authors (91.6%), exceeding Lotka's expectation, suggests limited continuity of individual contributions, a characteristic often observed in emerging fields. In parallel, the high average number of co-authors per article (7.39) reflects the complexity of integrating clinical, computational, and laboratory expertise, consistent with the widespread interdisciplinary diffusion of AI across scientific domains (Hajkowicz et al., 2023). Although international collaboration is present (23.5%), scientific leadership remains concentrated. This aligns with global evidence showing that AI research output and impact are disproportionately dominated by a small number of countries, particularly the United States and China (AlShebli et al., 2024). Persistent asymmetries in research capacity and collaboration structures between the Global North and Global South continue to shape the field (Ni et al., 2026), potentially introducing geographic bias and limiting the generalizability of findings across diverse healthcare settings.

The thematic evolution of the field reflects a progression from pandemic-driven research toward clinical implementation. Early research was strongly influenced by the COVID-19 pandemic, as indicated by the prominence of keywords such as COVID-19 and SARS-CoV-2, highlighting the role of artificial intelligence in rapid diagnosis, epidemic prediction, and healthcare system support during large-scale outbreaks (Wang et al., 2021). This was followed by a phase of technical consolidation, characterized by increased use of deep learning, retrospective datasets, and structured analytical approaches, reflecting the central role of machine learning and big data in healthcare applications (Ali et al., 2023). These developments indicate a shift toward more systematic data-driven methodologies and validation frameworks. More recent trends demonstrate a transition toward clinically oriented outcomes, including diagnosis, predictive modeling, and patient management, aligning with established AI functionalities in diagnosis, treatment, and monitoring (Ali et al., 2023). Overall, this progression reflects movement from methodological development toward clinically relevant implementation, supporting precision diagnostics and risk stratification.

The conceptual structure further supports a transition toward clinically integrated and patient-centered research. The increasing prominence of terms such as human, female, male, adult, and clinical laboratory reflects a shift toward real-world validation and patient-oriented applications. This trend aligns with the growing role of artificial intelligence in enhancing clinical workflows, improving diagnostic processes, and supporting patient engagement within healthcare systems (Topol, 2019). Multiple Correspondence Analysis demonstrates a primary axis separating observational and descriptive studies from implementation-focused research, with terms such as workflow, patient care, and electronic health record clustering within the application domain. This indicates system-level integration of AI into laboratory services, supported by evidence that deep learning models leveraging electronic health records can generate scalable and clinically relevant predictions across multiple outcomes (Rajkomar et al., 2018). However, translation into routine clinical practice remains limited, with persistent challenges related to validation, implementation, and generalizability (Kelly et al., 2019). These findings suggest that AI is increasingly positioned not only as a diagnostic tool but also as an operational component of healthcare delivery.

Highly cited studies further emphasize the importance of bridging methodological innovation with clinical relevance. Influential work highlights the integration of artificial intelligence with diverse clinical data sources, including imaging, electronic health records, and multi-omics approaches, to enhance real-world applicability (Esteva et al., 2019). In parallel, the growing emphasis on explainable artificial intelligence underscores the need for transparency, interpretability, and trust to enable safe and effective clinical adoption (Sadeghi et al., 2024). These developments indicate that research impact is driven not solely by algorithmic advancement but by demonstrable clinical utility and reliability. This perspective is reinforced by evidence that successful integration of AI into healthcare depends on its contribution to clinical workflows, system-level efficiency, and patient-centered care (Topol, 2019). Moreover, the incorporation of explainable AI into clinical decision support systems has shown potential to improve diagnostic precision and risk stratification, although challenges in real-world validation and usability remain (Abbas et al., 2025). Collectively, these findings underscore the importance of translational approaches that bridge advanced analytics with practical implementation in real-world healthcare settings.

CONCLUSION

This bibliometric analysis indicates that artificial intelligence research in clinical laboratories is rapidly expanding but remains at an early stage of maturity, with a clear shift toward clinically oriented implementation. Despite growing alignment with real-world applications, the field remains fragmented, with uneven global participation and leadership concentrated in a limited number of countries. Notably, research impact is increasingly driven by translational value rather than methodological novelty alone. Advancing the field will require robust validation, inclusive collaboration, and scalable integration to ensure clinically reliable and equitable implementation in healthcare systems.

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