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# Role of Artificial Intelligence in Clinical Laboratory Workflow Optimization: Review

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## Abstract

**Background:** The integration of Artificial Intelligence (AI) in clinical laboratories has emerged as a transformative force, promising enhanced workflow optimization and improved patient outcomes. As clinical testing increasingly consolidates, the need for efficient data management and decision-making processes has become paramount.

**Methods:** This review analyzes various AI methodologies applied in clinical laboratories, focusing on their role in pre-analytical, analytical, and post-analytical phases. We examined advancements in Laboratory Information Systems (LIS) that facilitate the collection and integration of vast healthcare data, emphasizing the use of machine learning (ML) algorithms for predictive analytics and operational efficiency.

**Results:** Findings indicate that AI tools have significantly improved the accuracy of laboratory results, enhanced diagnostic stewardship, and optimized test requests. Notable applications include the auto-validation of results, identification of sample mix-ups through delta checks, and predictive modeling for patient monitoring. The review

highlights successful case studies where AI integration has led to streamlined workflows and reduced turnaround times, ultimately benefiting patient care.

**Conclusion:** The implementation of AI in clinical laboratories is reshaping the landscape of laboratory medicine, enabling a shift from traditional practices to more dynamic, patient-centered approaches. Continuous advancements in AI technologies and data integration strategies are essential for overcoming existing challenges, such as data standardization and privacy concerns. Future efforts should focus on fostering collaboration between laboratory professionals and data scientists to maximize the potential of AI in enhancing clinical laboratory services.

**Keywords:** Artificial Intelligence, clinical laboratories, workflow optimization, machine learning, laboratory information systems.

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## 1. Introduction

In recent years, medical labs have significantly transformed, shifting towards the consolidation of clinical testing inside large facilities to increase volume and decrease expenses [1]. This business model paradigm centered on outsourcing laboratory testing has not met expectations; it has not shown a substantial reduction in total expenses [2]. It has been shown that, up to a threshold of one million tests per year, elevated costs are associated with volume. Beyond this level, the relationship between volumes and costs is non-linear, since laboratory organization has a greater influence on final costs than test volume does [2]. It was posited that the relationship between prices and test volumes was primarily maintained by the "traditional laboratory test," which has been extensively requested in recent decades and is well understood by clinicians who can accurately interpret its values [3].

Advancements in technology and organization, together enhanced understanding of human illness pathophysiology, have collectively transformed the perception of clinical laboratories into commodities. Laboratories have progressively transitioned from the "silos" concept to a more integrated and patient-centered approach. Various factors contribute to this transformation, with positive influences including diagnostic stewardship, advancements in molecular and genotypic testing, and creative technology, which provide more tailored laboratory findings [1, 3]. Conversely, the downsizing of laboratory-based point-of-care (POC) testing equipment and their integration with telemedicine underscores the essential function of labs in "near-patient" testing, indicating a transformative future role for clinical laboratories.

A transformative shift in clinical labs is contingent upon the digitization of processes, which is impacting all areas of healthcare, including medical laboratories. This force is propelled by several factors, including the seamless handling of vast data quantities, the facilitation of new technology systems for data integration, and, importantly, the extensive and effective use of artificial intelligence (AI). Although AI is not a novel concept

in computer science, its use has surged in recent years, mostly due to the processing power required to exploit the promise of these methodologies [4]. Nonetheless, inside hospitals and healthcare services, clinical labs generate a substantial volume of mostly high-quality information daily (e.g., patient outcomes), which serves as a valuable resource for training computer-based algorithms, including AI tools.

## 2. The importance of clinical labs in the proliferation of extensive healthcare data

Historically, clinical investigations have consistently included medical laboratory findings with demographic data. Although done under stringent criteria, these investigations were often constrained by challenges such as patient recruitment difficulties and limited resources among medical personnel. In recent years, the extensive proliferation of laboratory information systems (LIS) has facilitated the swift acquisition of patient findings, therefore providing researchers with vast amounts of retrospective data at no extra expense. Consequently, some kinds of clinical studies are transforming, with various models swiftly developing via data acquired from Laboratory Information Systems (LIS), particularly when the study aim is to correlate outcomes with positive or negative biochemical phenotypes [5]. Moreover, the digital revolution of healthcare now facilitates the integration of data from several disciplines and patients. The establishment of integrated data warehouses in healthcare institutions acknowledged as sources of "big data," has facilitated the application of AI tools for data analysis and other computational technologies, such as natural language processing (NLP), which may subsequently produce additional resources for patient care [5].

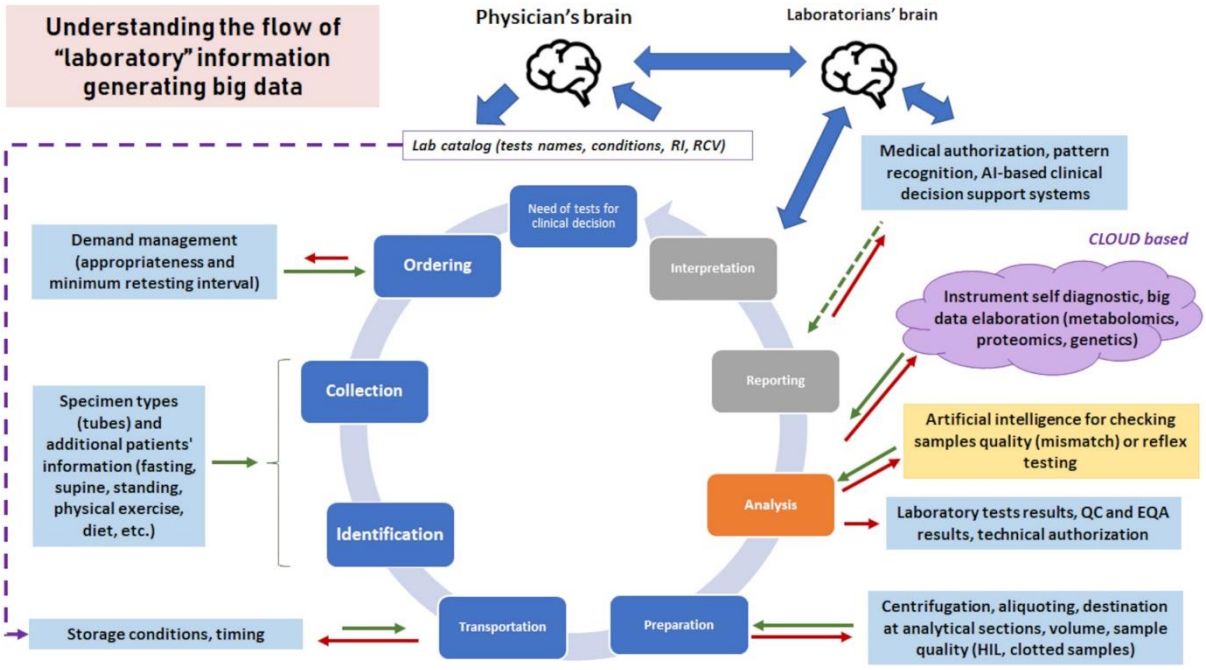
## 3. Revealing the dissemination of information in contemporary clinical labs

The laboratory testing delivery proposed 50 years ago by Lundberg [6], who originated the phrase "brain-to-brain turnaround time loop," was revisited in 2011 by Plebani et al. [7]. Since Lundberg initially articulated this notion, there has been a continuous rise in both the variety and volume of information produced for each patient during laboratory testing. Alongside clinical outcomes and demographic factors, LIS may include other pertinent compounding data, like internal quality control (instrumental) or external quality assessment (EQA) findings, as well as the time of test requests, blood collection, or transmission of exam results. Nevertheless, a comprehensive investigation uncovers a larger quantity of data produced daily by the clinical laboratory, even though most of this information is only partly documented in the LIS. The information may encompass pre-analytical attributes (e.g., retesting intervals, supplementary dietary data, lifestyle factors, sample storage conditions or handling, presence of hemolysis), analytical attributes (e.g., technical and medical validations, automated quality checks for samples or sample mismatches, instrumental self-diagnosis, or intricate data processing checks), and post-analytical attributes (e.g., recommendations from clinical decision support

systems based on patient test outcomes, physician visualization of results, and the duration for communicating critical test results).

**Figure 1.** An altered brain-to-brain loop diagram illustrating the information flow inside a clinical laboratory.

This data type has distinctive properties, including volume, velocity, diversity, and authenticity, but ultimately generates value for medical care, laboratory professionals, and manufacturers' technicians. Given that all these traits are ascribed to big data, it is plausible to assert that every laboratory generates huge data on a regular basis [8]. Moreover, labs consistently update the laboratory test catalog, accessible to laboratory staff, hospital doctors, and workers (Figure 1).




At now, several tools, ranging from basic "if-then" algorithms to advanced AI systems, have been effectively developed and, in some instances, included into the pre-analytical, analytical, or post-analytical stages of the brain-to-brain loop. Various informatics demand management methods developed and implemented guarantee the suitable test request in a certain scenario [9, 10]. AI was beneficial in interpreting test outcomes during COVID-19 quick testing [11]. Another instance of AI utilization in laboratory medicine is the identification of sample mix-ups by delta checks using machine learning technologies, which surpass the efficacy of relying on a solitary hematological metric, such as the MCV [12]. In another study, AI-based protocols for the auto-validation of laboratory results demonstrated a high concordance with laboratory professionals [13]. Additionally, other machine learning methodologies have been employed to predict thromboembolism in cancer patients, thereby enhancing collaborative efforts between clinicians and laboratories in identifying patients requiring monitoring for disease risk [14].

Improvements in laboratory capabilities for identifying molecular genotypic abnormalities, and metabolomic changes, and conducting proteomic analyses (such as MALDI-TOF/MS for amyloidosis detection) have enabled enhanced personalization of laboratory results, necessitating the establishment of new workflows. The substantial volume of information acquired necessitates appropriate infrastructures for data storage in compliance with national legislation for the requisite duration. Secondly, while findings are not always readily comprehensible, they need software that may include AI techniques and is often cloud-based, hence raising additional concerns surrounding data ownership and cloud storage duration. Third, several web-based resources, such as tools for analyzing uncommon point mutations in genetics or for identifying proteins from fragmentation patterns in proteomics, are often used by professionals in laboratory medicine using these technologies.

## 4. Artificial Intelligence encounters extensive laboratory data

AI has been proposed as an advocate for a persuasive pitch, transitioning from a conventional method centered on assessing efficacy in the average individual to tactics customized for the specific person. This change has been driven by the accessibility of longitudinal data, coupled with the use of adaptable machine-learning methodologies [15]. The primary catalyst for the current surge in expectations within the AI sector is the accessible abundance of extensive healthcare data [16].

In the laboratory, developments in LIS have facilitated the collection of substantial findings within a constrained timeframe, using few resources [17]. In most instances, it is essential to amalgamate laboratory data with supplementary clinical data from patients (e.g., diagnosis, illness recurrence, and comorbidities) for ML applications. Laboratory and clinical data must be linked both horizontally and vertically, with the former dimension about the longitudinal perspective of data acquired from various tests and exams performed on patients over time. Vertical integration includes medical records from laboratories, clinical records across many medical specialties (e.g., cardiology and radiology), and data from patients themselves (e.g., via wearable devices or linked diagnostic lab-on-skin testing) [18, 19].

The potential value of merging patients' information, now dispersed across various sections of the healthcare data warehouse, is hindered by the presence of disparate data formats [20]. Structured data sources, such as laboratory tests and patients' admission and discharge dates, can typically be seamlessly integrated using suitable software, whereas unstructured data sources, including clinical notes and observations gathered during hospitalization, are often heterogeneous, consisting of various data types lacking inherent organization. Concerning unstructured data, technologies like NLP approaches, sometimes cloud-based, may assist in extracting information from the free-form text of healthcare records; however, these systems have yet to be assessed in a context that mimics clinical practice [21]. Commercially developed classes of wearable medical devices are now attaining technical advancements that allow them to function as lab-on-a-chip systems, facilitating continuous monitoring of hospitalized patients. Portable

point-of-care (POC) systems are essential for outpatients necessitating close monitoring and quick clinical decisions in response to changes in key parameters. In certain contexts, existing wearable systems (e.g., consumer wearable devices) that continually monitor heart rate, body temperature, electrodermal activity, and motions may be used to assess vital signs. This data is used to instruct AI systems in predicting fluctuations in clinical laboratory test results, hence facilitating the identification of declines in a patient's vital condition [23].

## 5. Obstacles and drawbacks of AI integration in laboratory medicine

Two recent studies demonstrated the increasing use of data analytics and AI methodologies and models in laboratory medicine and other medical disciplines [5, 24]. The findings indicated a rising interest in AI, shown by a rise in publications from 2017 to 2021; nevertheless, only 8 out of 44 (18.2%) of the papers were from laboratory medicine organizations, while the remainder were authored by researchers from other fields. Numerous writers have delineated various restrictions [18, 25-27]. From a local perspective, the first drawback may be to the specialized expertise of AI inside the laboratory community, which is essential for stimulating new research and tackling implementation issues [28]. A recent online survey of stakeholders in laboratory medicine in the United States indicated that the majority of participants anticipate the value of AI shortly; however, essential prerequisites remain unmet, and the overall understanding of AI within the medical community is inadequate [28]. This aspect may be attributed to a broader notion including the laboratory's digital revolution, which also incorporates emerging fields such as clinical bioinformatics, communication improvement, interactive abilities, and informatics competencies [3, 29, 30]. Training designed to enhance the digital competencies of this group of laboratory medicine professionals necessitates recognizing and addressing the disparity in collaboration between educators and learners, with Scientific Societies also playing a significant role in this initiative. The second restriction may be the facilitation of straightforward access to patients' health records (e.g., diagnosis, comorbidities, clinical parameters, and therapeutic medications) [16]. For clinical usefulness, AI and ML systems must leverage the numerous reusability of data and clinical outcomes for expedited learning [20]. This contrasts with the typical procedure in clinical studies when laboratory findings are first correlated with patients' clinical data (e.g., illness), followed by the use of machine learning. This paradigm must be transcended to enable the implementation of ML, since ML algorithms may gain from ongoing refinement via more data, developing over time [20].

From a worldwide perspective, pertinent constraints to AI deployment include data quality, results uniformity, legal and privacy concerns, and IT security. Presently, AI techniques need extensive datasets, and often, outcomes cannot be achieved by an individual laboratory. Exchanging electronic patient records or other IT infrastructures, like as laboratory test results, may provide challenges; even when data are aligned with standardized patterns, it is not always feasible to integrate and evaluate the data

collectively [18]. Upon evaluating several laboratories, it is evident that only a restricted range of analytes is adequately standardized to guarantee compatibility [18, 31]. Consequently, the uniform coding of laboratory test names, attainable via the systematic analysis of identifiers' names and codes (LOINC), is critically significant. In addition to laboratory analysis, the resulting unit must be machine-readable to facilitate connectivity and the interchange of laboratory findings [25].

Moreover, despite attempts to standardize and harmonize, the measuring instruments used significantly affect some outcomes, and the utilization of device-specific target values obtained from EQA schemes can only be effective if disseminated in a designated database, such as EUDAMED [25]. Interpretative remarks, essential to laboratory reports, must be organized and categorized for effective summary and dissemination. Ethical and normative concerns are of paramount significance. For instance, patients' agreement for the use of their health data for specific treatments is invalid if employed for AI applications [32]. Moreover, standards must align with prevailing rules, including national laws, and data protection regulations such as the General Data Protection Regulation (GDPR) of 2018, the European Union Charter of Fundamental Rights, and other pertinent provisions [32].

It is essential to stress that although data scientists may build and create exceptional AI algorithms, the active involvement of laboratory specialists is crucial for delivering precise data analysis and interpretation throughout the whole process. The theoretical mathematical formulation of algorithms is inadequate for developing clinically useful algorithms, particularly when biological parameters are not assessed in the proper context, taking into account pertinent laboratory medicine concepts such as biological variability, analytical objectives, and analytical variability.

## 6. Conclusions

Laboratory workers are integral to all medical professions, aiding physicians and determining the appropriate test for each patient at the optimal moment. The notion of "clinical laboratory stewardship" includes all stages of the complete testing process and is a significant catalyst for the impending transformations in laboratory medicine, particularly the transition to a patient-centered approach. Simultaneously, technical breakthroughs and the digital revolution are enhancing precision medicine, which properly correlates patients with their particular profiles based on personal examinations and laboratory testing to their clinical outcomes.

The transformation in laboratory medicine from isolated entities to essential components for early diagnosis, prognosis, and personalized treatment can be effectively enhanced by artificial intelligence and its tools, such as machine learning. This evolution is driven by the extensive availability of big data in healthcare, including laboratory data, necessitating the emergence of new professionals in data science capable of converting raw data into advancements in patient care. While the competencies and skills of laboratory medicine specialists may never entirely encompass the intricate mathematical theoretical applications of machine learning, there is an imperative to bolster

collaboration between laboratory and AI experts, to orchestrate and regulate the processes, and to promote the adoption of suitable technologies. Otherwise, there is a danger of achieving a sterile environment, inundated with advanced technology that provides little benefit to either the laboratory or the patient.

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**المستخلص**

**الخلفية :**أصبح دمج الذكاء الاصطناعي (AI) في المختبرات السريرية قوة تحوّلية واعدة بتحسين سير العمل وتعزيز نتائج المرضى. ومع تزايد التركيز على دمج الفحوص السريرية، أصبحت الحاجة إلى إدارة البيانات بكفاءة واتخاذ القرارات السريعة أمرًا بالغ الأهمية.

**الطرق :**تحلل هذه المراجعة مختلف المنهجيات المستندة إلى الذكاء الاصطناعي التي يتم تطبيقها في المختبرات السريرية، مع التركيز على دورها في المراحل ما قبل التحليلية، والتحليلية، وما بعد التحليلية. تم فحص التطورات في أنظمة معلومات المختبرات (LIS) التي تسهل جمع ودمج البيانات الصحية الضخمة، مع التركيز على استخدام خوارزميات التعلم الآلي (ML) للتحليلات التنبؤية وتحسين الكفاءة التشغيلية.

**النتائج :**تشير النتائج إلى أن أدوات الذكاء الاصطناعي حسّنت بشكل كبير دقة النتائج المخبرية، وعززت توجيه التشخيص، وحسّنت طلبات الفحوص. تشمل التطبيقات البارزة التحقق الآلي من النتائج، وتحديد الأخطاء في العينات باستخدام فحوص دلتا، ونماذج التنبؤ لمراقبة المرضى. تسلط المراجعة الضوء على دراسات حالة ناجحة حيث أدى دمج الذكاء الاصطناعي إلى تحسين سير العمل وتقليل أوقات المعالجة، مما انعكس إيجابياً على رعاية المرضى.

**الاستنتاج :**يشكّل تطبيق الذكاء الاصطناعي في المختبرات السريرية تغييراً جوهرياً في مجال الطب المخبري، مما يتيح التحول من الممارسات التقليدية إلى نهج أكثر ديناميكية يتمحور حول المريض. إن التطورات المستمرة في تقنيات الذكاء الاصطناعي واستراتيجيات تكامل البيانات ضرورية للتغلب على التحديات الحالية، مثل توحيد البيانات ومخاوف الخصوصية. ينبغي أن تركز الجهود المستقبلية على تعزيز التعاون بين المتخصصين في المختبرات وعلماء البيانات لتعظيم الاستفادة من الذكاء الاصطناعي في تحسين الخدمات المخبرية السريرية.

**الكلمات المفتاحية :**الذكاء الاصطناعي، المختبرات السريرية، تحسين سير العمل، التعلم الآلي، أنظمة معلومات المختبرات.