

ORIGINAL RESEARCH

Open access

Transformer-Based Prediction Model for Laboratory Test Turnaround Delays Using Order Priority, Specimen Collection Time, Transport Route, Department Workload, Analyzer Availability, and Historical Processing Patterns

Claire Dupont^{1*}, Julien Martin¹

Abstract

Laboratory turnaround time is a core operational metric linking laboratory performance to clinical decision-making. Delays arise from interacting pre-analytical, analytical, and post-analytical factors that vary by order priority, specimen pathway, workload, and analyzer status. Most turnaround time monitoring remains retrospective, aggregated, and focused on average performance. Such monitoring does not estimate whether an individual test order is likely to become delayed under current operational conditions. This manuscript develops a conceptual transformer-based prediction model for estimating the probability of turnaround delay for each incoming laboratory test order. The model uses order priority, specimen collection time, transport route, department workload, analyzer availability, and historical processing patterns. A transformer encoder ingests timestamped processing milestones from the laboratory workflow, including order entry, specimen collection, transport, accessioning, analyzer loading, result generation, and verification. Static features such as order priority, test type, and transport route are fused with dynamic sequence features through attention-based integration. Conceptually, the model could identify orders at elevated risk of delay as soon as they enter the pre-analytical or analytical pipeline. Its predictions would be expected to support proactive prioritisation, specimen routing, workload balancing, and analyzer assignment. A transformer-based turnaround delay model could shift laboratory operations from retrospective monitoring toward proactive delay prevention. Prospective implementation studies would be needed to evaluate safety, reliability, workflow fit, and operational usefulness.

Keywords Clinical laboratory informatics, Turnaround time, Transformer model, Laboratory operations, Specimen transport, Analyzer availability

*Correspondence:

Claire Dupont
claire.dupont@gmail.com

¹ Department of Health Informatics and Data Systems, Faculty of Medicine, University of Bordeaux, Bordeaux, France

Introduction

Delayed laboratory results can compromise timely clinical decision-making in emergency departments, inpatient wards, and outpatient services, particularly when clinicians depend on laboratory evidence for disposition, diagnosis, triage, or treatment escalation. Studies linking laboratory turnaround time to emergency department length of stay and process efficiency show that laboratory delays are not merely internal operational issues but clinical flow constraints [1, 2]. Delays in cardiac markers, urgent chemistry panels, and other time-sensitive tests may affect clinical pathways in which

interpretation and action are time-dependent [3]. Because laboratory results often sit at the interface between diagnostic uncertainty and treatment decisions, prediction of delay risk at the individual order level is operationally meaningful [4, 5].

The clinical laboratory is a multi-stage production environment in which specimens move through order entry, collection, transport, accessioning, analysis, verification, and result reporting. Lean and quality-improvement studies have shown that bottlenecks can occur at several points in this chain, including specimen receipt, workflow layout, queue accumulation, and post-analytical release [6-8]. Traditional turnaround dashboards often summarize mean or median performance across tests, departments, shifts, or priority categories, but these aggregate summaries do not reveal whether a specific order is likely to miss an expected reporting window [9, 10]. A model that captures order-level context could therefore complement retrospective quality monitoring with prospective delay prediction.

Machine learning has increasingly entered laboratory medicine, with applications in autoverification, decision support, analytical quality processes, and broader laboratory informatics workflows [11-16]. Prior work on clinical chemistry turnaround prediction indicates that operational data can support predictive modelling of laboratory process duration, but many approaches remain limited when the workflow is represented as a static collection of features rather than a temporally ordered event chain [9]. Transformer architectures were originally developed for sequential representation learning and have since been adapted to structured healthcare records and time-series forecasting [17-22]. This creates a methodological opportunity to model laboratory orders as evolving sequences rather than fixed records.

The central thesis of this manuscript is that laboratory turnaround delay prediction should be formulated as a dynamic sequence-learning task. Each test order generates a temporally ordered trail of milestones, and the meaning of each milestone depends on what preceded it, what time it occurred, and what operational state surrounded it. A transformer-based model could attend to relevant events such as prolonged transport, delayed accessioning, workload surges, analyzer unavailability, or atypical hour-of-day patterns while updating the delay probability as new data arrive. Such a model would be designed not to replace laboratory managers but to provide timely, interpretable estimates of which orders require attention.

Background

Laboratory turnaround time and its components

Laboratory turnaround time usually spans pre-analytical, analytical, and post-analytical phases, each of which can introduce delay. The pre-analytical phase includes order placement, patient identification, specimen collection, labeling, and transport, while the analytical phase includes accessioning, analyzer loading, run time, and instrument-specific processing [6, 7, 23]. The post-analytical phase includes result verification, autoverification, manual review, and release to the electronic record [11, 13]. Quality-improvement studies suggest that effective turnaround management requires understanding where delay accumulates across these phases rather than treating TAT as a single undifferentiated interval [5, 8, 24].

Order priority and specimen transport dynamics

Order priority shapes the expected service standard for laboratory tests, with STAT orders requiring faster handling than routine orders and often triggering different transport or processing behaviours. Specimen transport adds spatial and logistical variability, because pneumatic tube systems, couriers, hand delivery, and outpatient collection pathways differ in reliability, batching, and susceptibility to congestion [23, 25]. Emergency and outpatient laboratory studies show that improvements in blood collection workflows and specimen identification can affect downstream timeliness, especially when transport and accessioning are closely coupled [1, 2, 10]. A delay model should therefore encode both priority class and transport route because two specimens with identical test types may have very different risk profiles depending on route and urgency [9, 24].

Workload and analyzer availability

Laboratory delay risk is strongly influenced by workload, queue length, instrument throughput, staffing patterns, and analyzer availability. Lean management studies indicate that workload imbalance, inefficient process layout, and batching can produce avoidable turnaround delays even when individual instruments perform correctly [6-8, 10]. Analyzer downtime, maintenance, calibration, quality-control review, and rerouting between instruments can further alter the time from accessioning to verified result [11, 13]. Because these factors vary over the day and across shifts, a useful prediction model should treat workload and analyzer state as time-varying operational features rather than static laboratory characteristics [9, 24].

Machine learning for laboratory operations

Machine learning has been proposed for several laboratory medicine tasks, including autoverification, error detection, result interpretation, and process optimization [12-16]. In the operations domain, turnaround prediction for clinical chemistry samples demonstrates that machine learning can be used to estimate process duration from laboratory workflow data [9]. However, many laboratory models are conceptually closer to tabular predictors than event-sequence models, which may limit their ability to learn how delay evolves as a specimen passes through successive milestones [14, 15]. A transformer-based formulation is attractive because it can combine historical patterns, current workload, and the observed milestone sequence within a single model architecture [19, 22].

Transformer models for sequential event data

Transformer models use attention mechanisms to identify relationships among elements in a sequence without relying exclusively on recurrence or fixed temporal windows [17]. Positional and temporal encodings allow the architecture to distinguish not only which events occurred but also their order, timing, and spacing, which is essential for laboratory workflows where elapsed time between milestones is clinically and operationally meaningful [18, 19]. Healthcare applications such as BEHRT, Med-BERT, and Hi-BEHRT illustrate how transformer-based models can represent structured longitudinal clinical events for prediction tasks [20-22]. These developments support adapting transformer encoders to laboratory event chains, where order milestones resemble a structured operational trajectory rather than free-text language.

Model Development Overview

High-level predictive pipeline

The proposed predictive pipeline would begin with real-time ingestion of laboratory information system, middleware, and specimen tracking events as each order progresses through the workflow. For each test order, the system would assemble a sequence of timestamped milestones and combine it with contextual features such as order priority, test type, route, workload, analyzer state, and historical time-of-day patterns [9, 23, 24]. A transformer encoder would update the representation of the order whenever a new event is logged, producing a current probability of delay and an estimate of remaining turnaround time. This pipeline follows the broader direction of laboratory informatics in which operational data streams are converted into actionable predictions rather than retrospective reports [11, 14].

Figure 1 illustrates the hierarchical architecture of the proposed transformer-based model, demonstrating how multimodal operational inputs and sequential laboratory events are integrated to generate real-time delay risk predictions.

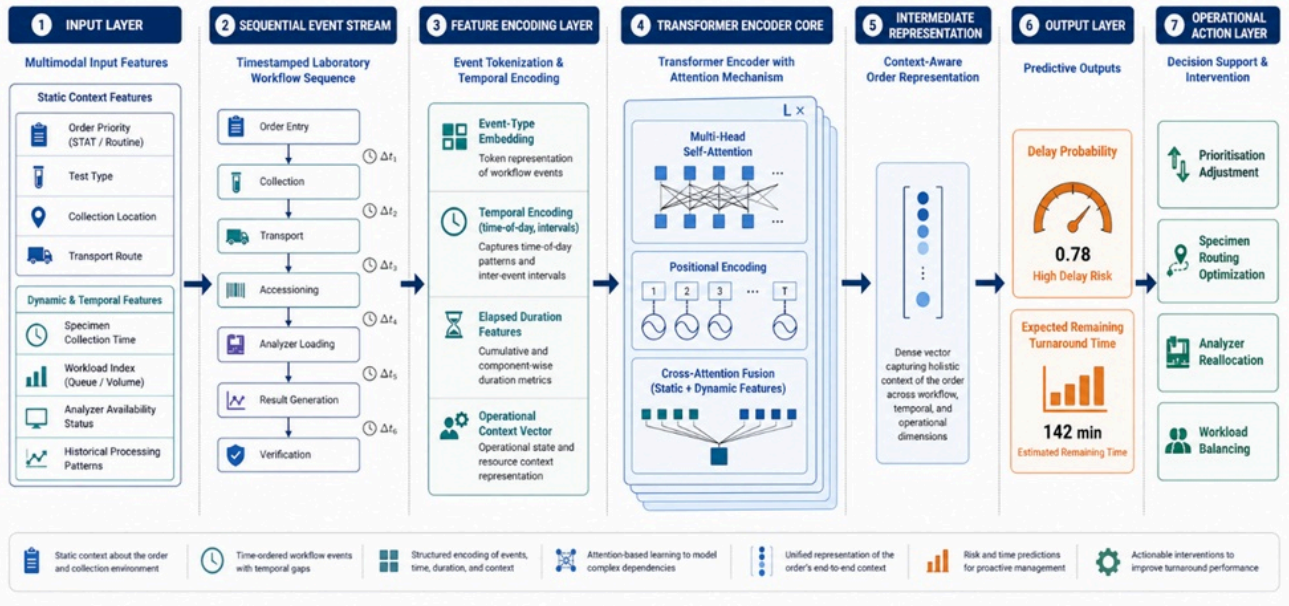


Figure 1. Transformer-based hierarchical pipeline for real-time prediction of laboratory test turnaround delay integrating sequential workflow events with static and dynamic operational features.

Core input features

The core input features would include order priority, specimen collection timestamp, collection location, transport route, test type, department workload index, analyzer availability status, and historical processing patterns for comparable orders. Order priority and test type provide clinical and operational expectations, while timestamp features capture hour-of-day, day-of-week, and shift effects that are known to influence laboratory process performance [2, 9, 10]. Workload indices could represent pending queue burden, recent order volume, or analyzer-specific load, whereas analyzer availability features could reflect downtime, maintenance, quality-control interruption, or rerouting status [11, 13]. Transport route features would encode whether the specimen used pneumatic tube delivery, courier transport, hand delivery, or outpatient collection workflows [23-25].

Table 1 summarizes the key static and dynamic input features used in the proposed transformer-based turnaround delay prediction model.

Table 1. Core Input Features for Transformer-Based Laboratory Turnaround Delay Prediction Model

Feature Category	Feature Name	Description	Type
Order Characteristics	Order Priority	Classification of urgency (e.g., STAT, routine) determining expected TAT	Static
Order Characteristics	Test Type	Laboratory test category influencing processing workflow	Static
Temporal Features	Specimen Collection Time	Timestamp used to derive temporal patterns (hour, shift)	Static
Temporal Features	Time-of-Day / Day-of-Week	Encoded temporal context reflecting operational variation	Dynamic
Location Features	Collection Location	Source of specimen (ED, inpatient, outpatient)	Static
Transport Features	Transport Route	Mode of delivery (pneumatic tube, courier, hand delivery)	Static

Workflow Features	Milestone Timestamps	Sequential workflow events (collection → verification)	Dynamic
Workload Features	Department Workload Index	Current workload level (queue size, incoming volume)	Dynamic
Workload Features	Analyzer Load	Utilization level of analyzers or instrument groups	Dynamic
Analyzer Status	Analyzer Availability	Operational state (active, downtime, maintenance, QC delay)	Dynamic
Historical Features	Historical Processing Patterns	Learned turnaround behavior from similar past orders	Dynamic
Derived Features	Elapsed Time Between Milestones	Time gaps between steps indicating potential delay accumulation	Dynamic

Design principles

The model should be sequence-aware, real-time updatable, probabilistic, and interpretable for laboratory managers. Sequence awareness is necessary because the same elapsed time can have different implications depending on whether the specimen is awaiting collection, in transport, accessioned, loaded on an analyzer, or pending verification [9, 6, 24]. Probabilistic output is preferable to a deterministic label because operational intervention requires prioritising orders under uncertainty rather than declaring delay as a fixed state. Interpretability is essential because laboratory staff must understand whether the alert is driven by transport delay, analyzer queue, workload surge, or a historical pattern before taking corrective action [12, 16].

Data Sources and Feature Engineering

Sequential milestone extraction from LIS

Sequential milestone extraction would use laboratory information systems, middleware, electronic health record order data, and specimen tracking logs to reconstruct the order trajectory. Relevant timestamps could include order entry, specimen collection, transport start, transport completion, laboratory receipt, accessioning, analyzer loading, result generation, verification, and release [9, 23, 24]. Not every laboratory captures all milestones with equal fidelity, so the extraction logic would need to distinguish directly observed events from inferred intervals. Prior work on laboratory workflow improvement and information-technology-enabled process redesign supports the feasibility of using operational timestamps to analyse and improve turnaround performance [8, 10, 24].

Static and dynamic feature construction

Feature construction would separate static order descriptors from dynamic operational variables. Static features could include order priority, test type, ordering location, collection location, specimen type, and intended transport route, whereas dynamic features could include current workload, pending queue burden, analyzer availability, and elapsed time since the previous milestone [9, 11, 13]. Time encodings would represent hour of day, day of week, shift period, and recurring historical patterns for similar test-priority combinations [19]. This distinction matters because static features define the expected service context, while dynamic features determine how delay risk evolves as the order moves through the laboratory system [2, 10].

Defining the delay ground truth

Delay ground truth would be defined by comparing observed turnaround time with laboratory-specific thresholds stratified by test type, order priority, and possibly clinical location. For example, STAT chemistry, routine chemistry, outpatient testing, and inpatient testing may require different delay definitions because their expected workflows and service

standards differ [1-3]. Orders with missing milestones would require careful handling, since an absent timestamp may indicate either incomplete logging or a true process deviation [5, 23]. A survival-informed formulation would allow orders still in progress to contribute partial information rather than being discarded until a final result is verified [26-28].

Transformer Architecture for tat Prediction

Input sequence representation

Each laboratory processing milestone would be represented as a token containing an event-type embedding, temporal embedding, elapsed-duration feature, and operational context vector. Event-type embeddings would distinguish order entry, collection, transport, accessioning, analyzer loading, result generation, and verification, while temporal embeddings would encode hour, day, shift, and interval since the previous event [17-19]. The duration-since-previous-milestone feature is particularly important because delay risk often appears as abnormal dwell time between expected steps rather than as a single isolated event [6, 9]. This representation would allow the model to learn that the significance of a milestone depends on where it occurs in the process and how long the preceding interval lasted [20-22].

Transformer encoder and cross-attention fusion

A transformer encoder would process the milestone sequence using self-attention so that each event representation can incorporate information from earlier and later observed events in the order trajectory. Static features such as order priority, transport route, test type, and collection location could be introduced through a parallel encoder or cross-attention mechanism, allowing the sequence representation to be conditioned on operational context [17-19]. This design is conceptually aligned with structured healthcare transformer models that integrate temporal clinical events to support downstream prediction [20-22]. In laboratory operations, such fusion would help the model distinguish a routine outpatient delay from a STAT inpatient delay even when the raw elapsed time appears similar [1, 2, 9].

Output head: delay probability and expected TAT

The output layer would produce a probability that the order will exceed its priority- and test-specific turnaround threshold, along with a predicted remaining turnaround time expressed conceptually rather than as a reported performance result. A classification head could support on-time versus delayed prediction, while a survival-informed head could estimate the evolving risk of delay for orders that have not yet completed processing [26-28]. This is important because many operational decisions occur before verification, when the final turnaround time is not yet known but the current sequence already contains useful evidence [9, 24]. The model output should therefore be treated as decision support for prioritisation, rerouting, or workload balancing rather than as an autonomous instruction to laboratory staff [12, 16].

Handling Sequential Events and Censored Orders

Partial sequences and real-time updating

The proposed model would accept partial milestone sequences, allowing prediction before the order has completed the full laboratory workflow. At order entry, the model could rely mainly on priority, test type, collection location, transport route, historical timing patterns, and current workload; after collection, transport, accessioning, or analyzer loading, the prediction could be updated using newly observed events [9, 23, 24]. This dynamic updating is important because laboratory delay risk may emerge gradually, such as when a specimen

or remains in an analyzer queue during a workload surge [6, 8]. Transformer-based sequence models are well suited to this setting because they can revise attention across the available event history whenever a new milestone is added [17, 19].

Censored data and survival-analysis integration

Orders still in progress create a censoring problem because their final turnaround time is unknown at the time of prediction. Rather than excluding such orders, a survival-analysis component could allow the model to learn from partial observation windows and estimate the evolving probability that a test will exceed its expected completion threshold [26–28]. Deep survival approaches are relevant because they support prediction from incomplete longitudinal information and can represent time-to-event risk under censoring [26, 28]. In the laboratory setting, this would allow the model to use orders awaiting verification, orders still in transport, or orders queued for analysis as informative cases rather than treating them as unusable records [9, 24].

Handling missing or erratic milestones

Laboratory event logs may contain missing, duplicated, delayed, or inconsistently recorded milestones, especially for transport start, transport completion, manual handoff, analyzer loading, or verification events. The model should therefore encode missingness explicitly and distinguish an absent milestone from a true zero-duration interval, because incomplete logging may itself reflect workflow variation [5, 23]. Attention mechanisms could help the model weight reliable events more strongly while reducing dependence on unavailable or erratic milestones, but this would still require rigorous data validation and local process knowledge [12, 16]. Operationally, the model should be designed to degrade gracefully when only partial LIS or middleware data are available, rather than assuming ideal timestamp fidelity [11, 14].

Model Interpretability and Operational Trust

Explaining delay predictions to laboratory managers

Delay predictions should be accompanied by explanations that indicate which observed milestones, elapsed intervals, or static features contributed most to the predicted risk. Attention-derived summaries could highlight prolonged transport, delayed accessioning, analyzer queue accumulation, unusual hour-of-day patterns, or workload pressure, while complementary feature-attribution methods could explain the influence of order priority, test type, transport route, or analyzer state [12, 16]. Interpretability is especially important in laboratory medicine because alerts must support accountable human action rather than obscure automated classification [14, 15]. A useful explanation would therefore translate model signals into operationally meaningful causes that laboratory managers can verify and address [6, 10].

Integration into laboratory dashboards

A real-time dashboard could display at-risk orders, predicted delay drivers, current workflow stage, and suggested operational review points. This interface would extend existing TAT monitoring by moving from retrospective average-based reporting to forward-looking identification of orders likely to breach service expectations [2, 9]. Dashboard integration should align with laboratory quality-improvement methods, where visual management, timely feedback, and process redesign are used to reduce avoidable delays [7, 8, 10]. The goal would not be to replace current LIS or middleware tools, but to add a predictive layer that directs human attention toward specimens most likely to benefit from intervention [11, 24].

Clinical Deployment and Laboratory Workflow Integration

Connection to LIS and real-time operation

In deployment, the model could run as a service connected to laboratory information systems, middleware, specimen tracking systems, and electronic health record order feeds. Each new event message, such as order entry, specimen collection, accessioning, analyzer loading, result generation, or verification, would trigger an updated sequence representation and revised delay probability [9, 23, 24]. Such integration is consistent with broader laboratory informatics

trends in which operational data streams support automation, autoverification, and decision support [11, 13]. To remain clinically useful, the model should operate within existing laboratory workflows and preserve human oversight for prioritisation, rerouting, and escalation decisions [12, 16].

Triggered interventions for high-delay orders

When an order exceeds a locally defined delay-risk threshold, the system could alert laboratory supervisors or bench staff and identify the most likely bottleneck. Possible interventions could include checking specimen location, expediting transport, reallocating work to an available analyzer, reviewing quality-control interruptions, or prioritising verification for time-sensitive orders [3, 6, 10]. The alerting logic should be calibrated to workflow capacity so that staff receive actionable signals rather than excessive notifications [14, 15]. Because STAT, routine, emergency, inpatient, and outpatient orders have different operational expectations, intervention rules should be aligned with test priority and clinical context [1, 2, 25].

Evaluation Strategy

Predictive performance metrics

Evaluation should assess delay classification, time-to-event prediction, remaining-turnaround estimation, and calibration. Suitable metrics could include area under the receiver operating characteristic curve for binary delay prediction, concordance-based metrics for survival-informed outputs, mean absolute error for turnaround estimation, and calibration plots comparing predicted and observed delay risk [26–28]. Metrics should be interpreted as validation criteria rather than as claimed results, because the present manuscript is a conceptual model description and does not report experiments. Evaluation should also stratify performance by order priority, test type, location, route, workload period, and analyzer status to ensure that the model does not perform well only in aggregate [1, 3, 9].

Temporal and external validation

Temporal validation would train the model on earlier historical periods and assess performance prospectively on later periods, thereby testing whether it remains useful when workload, staffing, routing, or analyzer conditions change. External validation at another hospital laboratory would be important because turnaround workflows differ across sites, including differences in transport systems, middleware, staffing models, analyzer platforms, and reporting rules [2, 4, 5]. Laboratory machine-learning recommendations emphasize that predictive systems should be evaluated for generalizability, data quality, and clinical workflow fit before routine deployment [12, 16]. A transformer model for TAT delay prediction should therefore be assessed not only for statistical discrimination but also for robustness across operational environments [19, 22].

Operational impact assessment

Operational impact should be assessed by examining whether model-triggered interventions could reduce avoidable TAT outliers, improve STAT compliance, support workload redistribution, and improve staff situational awareness. Quality-improvement studies in laboratory medicine show that process redesign, information technology, and Lean methods can improve timeliness, but predictive modelling adds a prospective layer by identifying risk before the delay is complete [7, 8, 10, 24]. Staff feedback would be important because laboratory personnel must judge whether alerts are understandable, timely, and actionable within real workflow constraints [12, 14]. Impact assessment should also monitor unintended consequences, such as over-prioritising predicted high-risk orders at the expense of routine throughput or increasing alert fatigue [15, 16].

Limitations

Data granularity and milestone fidelity

A major limitation is that not all laboratory information systems capture transport, handoff, analyzer loading, or manual review milestones with the precision required for high-quality sequence modelling. Missing or noisy timestamps could obscure whether delay occurred during collection, transport, accessioning, analysis, verification, or reporting [5, 23]. Middleware and LIS integration may improve timestamp availability, but event definitions can vary by site and may change after workflow redesign or software updates [11, 24]. For this reason, local data auditing and milestone harmonisation would be necessary before a transformer model could be used as a reliable operational decision-support tool [12, 16].

Generalizability across test types and laboratories

A model trained on one laboratory service line may not generalise to another because chemistry, hematology, microbiology, molecular diagnostics, and pathology workflows differ in processing time, batching, analyzer dependency, manual review burden, and reporting expectations. Similarly, a model trained in a hospital with pneumatic tube transport and high automation may not transfer directly to a site relying on couriers, manual accessioning, or different analyzer platforms [11, 23, 24]. Transformer models can learn flexible sequence representations, but they still require local validation, recalibration, and potentially fine-tuning when operational structure changes [19–22]. Generalizability should therefore be treated as an empirical deployment question rather than an assumed property of the architecture [12, 16].

Conclusion

A transformer-based model for laboratory turnaround delay prediction would conceptualize each test order as a dynamic sequence of operational events. By integrating order priority, specimen collection time, transport route, workload conditions, analyzer availability, and historical processing patterns, the model could estimate delay risk as the specimen moves through the laboratory pipeline.

The major strength of this approach is its sequence-aware design. Rather than relying only on static order descriptors or retrospective average turnaround summaries, the model could update predictions whenever a new milestone becomes available and provide interpretable attribution for the likely source of delay.

Several challenges remain before such a model could be used safely in clinical laboratory operations. These include inconsistent timestamp granularity, missing transport or analyzer events, cross-site variation in workflow design, evolving service standards, and the need to evaluate whether alerts improve decisions rather than merely increasing notification burden.

Future work should prioritise pilot deployments in high-volume hospital laboratories where delays have direct clinical and operational consequences. Standardised benchmarks for turnaround-delay prediction would also help compare modelling approaches, promote reproducibility, and guide responsible implementation in laboratory informatics.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 25 Sep 2022

Revised: 22 Oct 2022

Accepted: 13 Nov 2022

Published online: 25 February 2023

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Kaushik N, Khangulov VS, O'Hara M, Arnaout R. Reduction in laboratory turnaround time decreases emergency room length of stay. *Open Access Emerg Med.* 2018;10:37-45.
<https://doi.org/10.2147/OAEM.S152987>.
- Vrijzen BE, Haitjema S, Westerink J, Hulsbergen-Veelken CA, van Solinge WW, Ten Berg MJ, et al. Shorter laboratory turnaround time is associated with shorter emergency department length of stay: a retrospective cohort study. *BMC Emerg Med.* 2022;22(1):207.
<https://doi.org/10.1186/s12873-022-00758-z>.
- Wang H, Wang X, Wang K, Duan X, Jiang W, Tang B, et al. Evaluation of a cardiac troponin process flow at the chest pain center with the shortest turnaround time. *J Clin Lab Anal.* 2022;36(4):e24335.
<https://doi.org/10.1002/jcla.24335>.
- Shiferaw MB, Yismaw G. Magnitude of delayed turnaround time of laboratory results in Amhara Public Health Institute, Bahir Dar, Ethiopia. *BMC Health Serv Res.* 2019;19(1):240.
<https://doi.org/10.1186/s12913-019-4087-2>.
- Dawande PP, Wankhade RS, Akhtar FI, Noman O, Dawande P, Wankhade R. Turnaround time: an efficacy measure for medical laboratories. *Cureus.* 2022;14(9):e28815.
<https://doi.org/10.7759/cureus.28815>.
- Lou AH, Elnenaie MO, Sadek I, Thompson S, Crocker BD, Nassar BA. Multiple pre- and post-analytical lean approaches to the improvement of the laboratory turnaround time in a large core laboratory. *Clin Biochem.* 2017;50(15):864-9.
<https://doi.org/10.1016/j.clinbiochem.2017.06.015>.
- Inal TC, Goruroglu Ozturk O, Kibar F, Cetiner S, Matyar S, Daglioglu G, et al. Lean six sigma methodologies improve clinical laboratory efficiency and reduce turnaround times. *J Clin Lab Anal.* 2018;32(1):e22180.
<https://doi.org/10.1002/jcla.22180>.

Gupta S, Kapil S, Sharma M. Improvement of laboratory turnaround time using lean methodology. *Int J Health Care Qual Assur.* 2018;31(4):295-308.
<https://doi.org/10.1108/IJHCQA-08-2016-0113>.

Tsai ER, Demirtas D, Hoogendijk N, Tintu AN, Boucherie RJ. Turnaround time prediction for clinical chemistry samples using machine learning. *Clin Chem Lab Med.* 2022;60(12):1902-10.
<https://doi.org/10.1515/ccm-2022-0633>.

Ibrahim I, Sultan M, Yassine OG, Zaki A, Elamir H, Guirguis W. Using Lean Six Sigma to improve timeliness of clinical laboratory test results in a university hospital in Egypt. *Int J Lean Six Sigma.* 2022;13(5):1159-83.
<https://doi.org/10.1108/IJLSS-10-2021-0184>.

Naugler C, Church DL. Automation and artificial intelligence in the clinical laboratory. *Crit Rev Clin Lab Sci.* 2019;56(2):98-110.
<https://doi.org/10.1080/10408363.2018.1561648>.

De Bruyne S, Speeckaert MM, Van Biesen W, Delanghe JR. Recent evolutions of machine learning applications in clinical laboratory medicine. *Crit Rev Clin Lab Sci.* 2021;58(2):131-52.
<https://doi.org/10.1080/10408363.2020.1797679>.

Wang H, Wang H, Zhang J, Li X, Sun C, Zhang Y. Using machine learning to develop an autoverification system in a clinical biochemistry laboratory. *Clin Chem Lab Med.* 2021;59(5):883-91.
<https://doi.org/10.1515/ccm-2020-1294>.

Rabbani N, Kim GY, Suarez CJ, Chen JH. Applications of machine learning in routine laboratory medicine: current state and future directions. *Clin Biochem.* 2022;103:1-7.
<https://doi.org/10.1016/j.clinbiochem.2022.02.006>.

Zhang L, Hu ZD. Clinical applications of machine learning in pre-analytical, analytical and post-analytical phases of laboratory medicine: a narrative review. *AME Med J.* 2022;7:35.
<https://doi.org/10.21037/amj-21-96>.

Master SR, Badrick TC, Bietenbeck A, Haymond S. Machine learning in laboratory medicine: recommendations of the IFCC working group. *Clin Chem.* 2023;69(7):690-8.

Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. *Adv Neural Inf Process Syst.* 2017;30:5998-6008.

Devlin J, Chang MW, Lee K, Toutanova K. BERT: pre-training of deep bidirectional transformers for language understanding. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*. 2019;4171-86.

Lim B, Arik SO, Loeff N, Pfister T. Temporal fusion transformers for interpretable multi-horizon time series forecasting. *Int J Forecast.* 2021;37(4):1748-64.
<https://doi.org/10.1016/j.ijforecast.2021.03.012>.

Li Y, Rao S, Solares JRA, Hassaine A, Ramakrishnan R, Canoy D, et al. BEHRT: transformer for electronic health records. *Sci Rep.* 2020;10(1):7155.
<https://doi.org/10.1038/s41598-020-62922-y>.

Rasmy L, Xiang Y, Xie Z, Tao C, Zhi D. Med-BERT: pretrained contextualized embeddings on large-scale structured electronic health records for disease prediction. *NPJ Digit Med.* 2021;4(1):86.
<https://doi.org/10.1038/s41746-021-00455-y>.

Li Y, Mamouei M, Salimi-Khorshidi G, Rao S, Hassaine A, Canoy D, et al. Hi-BEHRT: hierarchical transformer-based model for accurate prediction of clinical events using multimodal longitudinal electronic health records. *IEEE J Biomed Health Inform.*

2023;27(2):1106-17.

<https://doi.org/10.1109/JBHI.2022.3224620>.

Wu LF, Zhuang GH, Hu QL, Zhang L, Luo ZM, Lv YJ, et al. Using information technology to optimize the identification process for outpatients having blood drawn and improve patient satisfaction. *BMC Med Inform Decis Mak.* 2022;22(1):61.

<https://doi.org/10.1186/s12911-022-01782-x>.

Zhang L, Liu ZH, Lv YJ, Fu S, Luo ZM, Guo ML. Comprehensive improvements in the emergency laboratory test process based on information technology. *BMC Med Inform Decis Mak.* 2023;23(1):292.

<https://doi.org/10.1186/s12911-023-02374-8>.

Fu S, Wu XG, Zhang L, Wu LF, Luo ZM, Hu QL. Service quality improvement of outpatient blood collection by lean management. *Patient Prefer Adherence.* 2021;15:1537-43.

<https://doi.org/10.2147/PPA.S312524>.

Katzman JL, Shaham U, Cloninger A, Bates J, Jiang T, Kluger Y. DeepSurv: personalized treatment recommender system using a Cox proportional hazards deep neural network. *BMC Med Res Methodol.* 2018;18(1):24.

<https://doi.org/10.1186/s12874-018-0482-1>.

Lee C, Zame W, Yoon J, Van Der Schaar M. DeepHit: a deep learning approach to survival analysis with competing risks. In: *Proc AAAI Conf Artif Intell.* 2018;32(1):2314-21.

<https://doi.org/10.1609/aaai.v32i1.11842>.

Lee C, Yoon J, Van Der Schaar M. Dynamic-DeepHit: a deep learning approach for dynamic survival analysis with competing risks based on longitudinal data. *IEEE Trans Biomed Eng.* 2020;67(1):122-33.

<https://doi.org/10.1109/TBME.2019.2909027>.