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Conceptual Model for Reducing Diagnostic Turnaround Time through Workflow Optimization and Staff Capacity Building

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Abstract
Diagnostic turnaround time (TAT) is one of the most visible indicators of clinical laboratory performance and one of the most persistent sources of dissatisfaction among clinicians and patients. Despite four decades of research since the articulation of the brain-to-brain loop, laboratories in many health systems continue to report total TAT well beyond agreed targets, with the greater share of delay occurring outside the analytical phase. Two broad families of intervention dominate the improvement literature. The first is workflow optimization, which applies Lean, Six Sigma, value stream mapping and automation to remove non-value-adding steps. The second is staff capacity building, which applies competency-based training, mentorship and quality management education to strengthen the people who run the process. These two families are usually studied and implemented separately, and each shows a characteristic failure mode when applied alone: redesigned workflows decay when staff lack the competence or motivation to sustain them, and trained staff underperform when embedded in a process that structurally prevents timeliness.
This paper develops the Integrated Workflow and Capacity Optimisation (IWCO) model, a conceptual framework that treats workflow redesign and human capacity development as two interdependent levers acting on a common set of phase-specific TAT outcomes. The model is derived from a narrative synthesis spanning the turnaround time literature and the adjacent literatures on diagnostic facility design, equipment and utility reliability, safety and process discipline, information systems and data governance, diagnostic supply chains and clinical service delivery. It is grounded in Donabedian's structure-process-outcome logic, Lean thinking, the theory of constraints, socio-technical systems theory, human capital theory and Kirkpatrick's evaluation hierarchy. It specifies six domains, seventeen constructs, eight testable propositions, a set of operational indicators, and a five-phase implementation sequence suitable for resource-constrained laboratories. The model is offered as a basis for empirical validation rather than as a validated instrument, and its principal contribution is to make explicit the interaction effects that single-lever interventions leave unexamined.

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1. Introduction

Laboratory medicine informs a large proportion of clinical decisions while consuming a modest proportion of hospital budgets, which makes the timeliness of laboratory information a high-leverage determinant of care quality. Timeliness is conventionally captured by turnaround time, defined most often as the interval from the ordering of a test to the reporting of its result (Hawkins, 2007). TAT is not simply an operational convenience. Delayed results prolong emergency department stays, defer therapeutic decisions, encourage duplicate ordering, extend length of stay and, in acute presentations such as sepsis, myocardial infarction and obstetric haemorrhage, can plausibly alter outcomes. The clinical dependence on timely laboratory information is visible across the disease spectrum, from cardiovascular risk stratification, where the value of an index lies in early detection and repeat monitoring (Okwah, 2022), to infection management, where antimicrobial choice cannot be narrowed until susceptibility data arrive (Omaghomi *et al*., 2022).

The conceptual foundation for thinking about TAT was laid by Lundberg (1981), whose brain-to-brain loop described laboratory testing as a continuous cycle that begins with a clinical question in the mind of the ordering clinician and closes only when an action is taken on the basis of the reported result. The loop comprises ordering, collection, identification, transportation, preparation, analysis, reporting, interpretation and action. Plebani *et al*. (2011), reviewing the concept forty years on, observed that technological advance has compressed the analytical segment of the loop dramatically while leaving the pre-analytical and post-analytical segments comparatively untouched, precisely because those segments depend on human coordination across organisational boundaries rather than on instrumentation.

That asymmetry is visible in contemporary empirical work. Phase-wise studies consistently attribute the majority of total TAT to non-analytical activity, with pre-analytical delay alone frequently accounting for more than half of the total interval. Where laboratories report failure to meet institutional targets, the causes named are rarely analytical: high and uneven workload, interruptions to the laboratory information system, power failure, specimen transport, phlebotomy scheduling, equipment downtime, and gaps in staff knowledge, attitude and practice regarding TAT itself (Gebreyes *et al*., 2020). Each of these determinants belongs to a different literature. Facility layout and spatial planning are treated in the healthcare infrastructure literature (Ogbete *et al*., 2018), equipment availability in the maintenance engineering literature (Adaramola *et al*., 2018), procedural adherence under pressure in the safety management literature (Obriki and Arumosoye, 2020), data capture in the health informatics literature (Nnaji and Akinlolu, 2022), and consumable availability in the diagnostic supply chain literature (Eze *et al*., 2022a). A model of TAT that draws on only one of these bodies of work will necessarily be partial.

Two intervention traditions dominate practice. The workflow tradition treats prolonged TAT as a process defect and applies industrial engineering tools to it. Inal *et al*. (2018), applying Lean Six Sigma to a hospital reception area, eliminated more than three hours of non-value-adding work per day and reduced stat sample TAT from 68 to 59 minutes while cutting error-prone steps from 30 per cent to 3 per cent. Comparable results are reported from adaptations of Lean Six Sigma designed for resource-constrained organisations, where full-scale deployment is not feasible and lighter-weight variants of the Define, Measure, Analyze, Improve, Control cycle are used instead (Ambali *et al*., 2021; Lokesh *et al*., 2020). The same methodology has been applied to hospital registration and admission, indicating that its scope extends beyond the bench to the administrative steps that bracket it (Bhat *et al*., 2014).

The capacity tradition treats prolonged TAT as a competency and management defect. The Strengthening Laboratory Management Toward Accreditation programme, a competency-based training model using short courses paired with work-based improvement projects and on-site mentorship, produced substantial and sustained gains in quality management scores across hundreds of laboratories in resource-limited settings, and its validation pilot recorded improvements in patient flow and turnaround time (Yao *et al*., 2014b). Parallel findings appear in the professional development literature, where competence in managing complex casework is shown to depend on sustained development rather than initial qualification (Yeboah *et al*., 2019).

The problem addressed in this paper is that these traditions are largely parallel rather than integrated. Workflow studies report process metrics and treat staff as an implementation constraint. Capacity studies report competency and accreditation metrics and treat workflow as a downstream consequence. Neither literature specifies how the two interact, under what conditions one substitutes for or amplifies the other, or why interventions of either type so often regress after the improvement team withdraws. Practitioners are therefore left without a framework that tells them how to sequence, balance and sustain the two kinds of investment, which matters most in exactly those settings where both process design and workforce competence are weak and resources for either are scarce (Ilodigwe and Adesemoye, 2019b).

This paper therefore sets out to develop a conceptual model explaining how workflow optimization and staff capacity building jointly reduce diagnostic turnaround time. It does so in four moves. It reconceptualises TAT as a phase-structured, multi-actor process outcome rather than a single laboratory metric. It identifies, from the workflow, infrastructure, reliability, safety, informatics, supply chain and capacity literatures, the determinants of prolonged TAT and the mechanisms through which each family of intervention acts on them. It specifies the constructs, interaction paths and boundary conditions of an integrated model, together with a set of testable propositions and operational indicators. And it proposes a phased implementation sequence for applying the model in practice. The questions that organise the argument are which components of the total testing process contribute most to delay and through what mechanisms, how each lever acts on those components, what interaction exists between the two and what that interaction implies for sequencing and sustainability, and which structural and contextual conditions moderate the whole relationship.

The model addresses hospital-based diagnostic services in clinical chemistry, haematology, microbiology and anatomic pathology. It is concerned with the interval from test ordering to result availability and clinician acknowledgement, and it treats the clinical action step of the brain-to-brain loop as an outcome rather than as a construct to be managed. Imaging turnaround is structurally analogous, and automated image analysis raises comparable questions about the boundary between machine output and validated report (Ejofodomi *et al*., 2014), but imaging is not modelled here. The paper is conceptual: it synthesises published evidence and theory rather than reporting primary data. For managers it offers a lens for deciding whether a given TAT problem is a process problem, a competency problem, or a coupled problem requiring simultaneous action; for researchers it converts a diffuse literature into falsifiable propositions; and for accrediting bodies it clarifies why TAT requirements written into standards such as ISO 15189 are met inconsistently even where training or automation has been funded, and identifies the measurement infrastructure without which neither lever is sustainable (Ilodigwe and Adesemoye, 2021).

Several terms are used in specific senses throughout. Diagnostic turnaround time is the elapsed interval between the point at which a test is ordered and the point at which its result becomes available to the ordering clinician. The total testing process is the full sequence of activities in the brain-to-brain loop, spanning pre-pre-analytical, pre-analytical, analytical, post-analytical and post-post-analytical phases. Workflow optimization refers to the systematic redesign of the sequence, layout, timing, batching and allocation of tasks within that process so as to reduce non-value-adding activity, waiting and rework. Staff capacity building refers to the planned development of individual and collective competence, authority and motivation among laboratory and interfacing personnel, comprising technical skill, quality management competence, mentorship, supervision, workload adequacy and retention. Process discipline denotes the degree to which a redesigned workflow is executed as designed in the absence of direct supervision, and absorptive capacity denotes the capacity of a unit to recognise the value of new operational knowledge, assimilate it and apply it to its own work (Cohen and Levinthal, 1990).

2. Turnaround Time and Its Determinants

2.1. Conceptualising Diagnostic Turnaround Time

There is no single definition of TAT, and this is itself a source of measurement confusion. Laboratories most commonly report intra-laboratory TAT, from specimen receipt to result validation, because those timestamps are readily available in the laboratory information system. Clinicians, by contrast, experience therapeutic TAT, from the moment they decide a test is needed to the moment they can act on it. The gap between the two definitions is where much of the delay lives, and reporting the narrower metric can allow a laboratory to record acceptable performance while its users experience unacceptable delay (Hawkins, 2007). The same measurement asymmetry is documented in hospital operations more broadly, where the interval that matters clinically is rarely the interval that is instrumented (Nnaji and Akinlolu, 2022).

For modelling purposes, TAT is best decomposed into five segments, as set out in Table 1.

Table 1: Phase decomposition of the total testing process.

Segment	Interval	Principal actors
Pre-pre-analytical	Clinical question to order entry	Clinician, ward staff
Pre-analytical	Order entry to specimen accessioning	Phlebotomist, porter, receptionist
Analytical	Accessioning to raw result generation	Laboratory scientist, analyser
Post-analytical	Result generation to validation and release	Scientist, pathologist, LIS
Post-post-analytical	Release to clinician acknowledgement	Clinician, LIS, communication system

Decomposition matters because the levers that act on each segment differ. Automation compresses the analytical segment; it does nothing for the pre-analytical segment, which is governed by scheduling, transport and identification practice. It follows that a laboratory reporting only the analytical interval can improve that figure indefinitely without the clinician noticing any change.

2.2. The Total Testing Process as the Unit of Analysis

Barth (2012) argues that accreditation frameworks have progressively shifted responsibility to laboratories for the extra-analytical phases, an area many laboratory staff find unfamiliar because it lies partly outside their physical and organisational control. Two implications follow: the unit of analysis must be the process rather than the laboratory, and capacity building must extend beyond bench technique to boundary-spanning competencies such as negotiating with wards, specifying transport standards and communicating critical results, which are competencies of coordination rather than of technique (Lilian *et al*., 2020).

Plebani and Lippi (2011) add a further consideration: the loop is only closed when the result is acted upon, yet feedback about whether that occurred is rarely collected. A laboratory that never learns what happened to its results has no reliable basis for prioritising which turnaround times matter most. This restates, at the level of a single test, the more general observation that scientific and technical innovation fails to improve patient outcomes where the delivery infrastructure that carries it to the bedside is weak (Ilodigwe and Adesemoye, 2019b).

2.3. Empirical Evidence on TAT Performance and Its Determinants

Studies from a range of settings converge on a consistent picture, confirming across further settings the phase-wise pattern already established in Section 1, whereby non-analytical activity accounts for the bulk of total TAT. Root cause analyses repeatedly identify the same operational determinants: batching of specimens for transport, concentration of phlebotomy in a narrow morning window that creates an arrival surge, manual data entry, unstandardised labelling, analyser downtime and maintenance delay, deferred validation because a validating officer is unavailable, and interruption of information systems or power supply.

In resource-constrained settings these determinants are compounded. Gebreyes *et al.* (2020), studying tertiary hospitals in Ethiopia, found overall achievement of chemistry and haematology TAT targets to be poor and attributed the shortfall to high workload, information system problems, power interruption and specimen collection timing, while also documenting that only around three in five staff, approximately 60 per cent, demonstrated adequate knowledge of TAT, and a similarly limited proportion demonstrated adequate practice. Petti *et al.* (2006) had earlier characterised weak laboratory medicine as a structural barrier to effective health care in Africa, citing shortages of trained personnel alongside infrastructure deficits. Studies of histopathology services in Nigeria report mean reporting times measured in days rather than hours, with recuts, regrossing, reagent stock-outs and inadequate supervision of newly hired technical staff among the causes of delay.

Two features of this evidence matter. The determinants named are simultaneously process attributes and human attributes, and this pattern of determinants is consistent with a reciprocal loop in which high workload degrades adherence and poor adherence generates rework that in turn increases workload, although the studies cited establish the individual determinants rather than testing this reciprocal loop directly. The sections that follow examine the literatures addressing them in turn.

2.4. Diagnostic Infrastructure and the Built Environment

The physical and organisational infrastructure within which a laboratory operates sets the outer bound on achievable TAT. Models developed for emerging and resource-constrained systems argue that diagnostic capacity should be planned as a service system rather than a set of buildings (Aminu-Ibrahim *et al*., 2018), and that capital project delivery arrangements determine whether it is realised as designed (Aminu-Ibrahim *et al*., 2019). Expansion into underserved and rural regions changes the pre-analytical geography of a whole catchment, since peripheral turnaround is dominated by transport distance rather than bench time (Aminu-Ibrahim *et al*., 2020). Programme management approaches address the sequencing problem when several facilities are built at once (Aminu-Ibrahim *et al*., 2021), and design work for pandemic response shows how surge requirements reshape layout and capacity assumptions (Aminu-Ibrahim *et al*., 2022).

Several strands bear directly on the phase structure of TAT. Spatial planning determines the distance a specimen travels between accessioning, preparation and analysis, and optimisation of laboratory layout is associated with gains in diagnostic accuracy, safety and clinical throughput simultaneously (Ogbete *et al*., 2018). Design standards for molecular and pathology environments impose containment and workflow constraints that cannot be removed by process redesign alone (Ogbete *et al*., 2019). Blood collection network design fixes the geography and scheduling of the pre-analytical phase (Ogbete *et al*., 2022). Materials selection and energy strategy affect environmental stability and therefore analyser performance (Ogbete *et al*., 2020), and risk-managed construction approaches determine whether new capacity arrives on time and functions as intended (Ogbete *et al*., 2021).

The wider built environment literature supplies the analytic methods behind these judgements. Frameworks for evaluating efficiency in building design provide the basis for assessing whether a given layout supports its intended operational pattern (Nwafor *et al*., 2019b), while comparative morphological studies show how building form conditions circulation and adjacency (Nwafor *et al*., 2018a). Climatic variables are shown to drive building energy demand and therefore the cost and reliability of environmental control (Nwafor *et al*., 2018b), and quantitative evaluation of locally sourced materials addresses the trade-off between capital cost and long-run performance that constrains laboratory construction in low-resource settings (Nwafor *et al*., 2019c). Resilience-oriented architectural interventions address the exposure of facilities to flooding and other disruption that interrupts service continuity (Nwafor *et al*., 2019a), socioeconomic analysis explains why affordability constraints shape what is actually built rather than what is specified (Gil-Ozoudeh *et al*., 2018), and evaluation of public-private partnership frameworks addresses the financing arrangements through which much health infrastructure is now delivered (Uduokhai *et al*., 2022). For the present model, the conclusion is that infrastructure operates as a moderator: it does not by itself produce short turnaround times, but it determines the range within which process and capacity interventions can operate.

2.5. Equipment Reliability, Utilities and the Operating Environment

Analyser downtime and power interruption appear in almost every root cause analysis of prolonged TAT, yet they are usually treated as background conditions rather than as managed variables. The maintenance engineering literature treats them as the latter. The transition from reactive to predictive maintenance is documented as a measurable shift in availability rather than a change of vocabulary (Sunday *et al*., 2020), and condition monitoring in critical infrastructure demonstrates the diagnostic techniques that make it possible (Adaramola *et al*., 2018). Predictive modelling of failure using operational data extends the same logic to systems where instrumented monitoring is limited (Mayo *et al*., 2021). Sensor-based fault detection in building services applies directly to the environmental systems on which analysers depend (Sunday and Omoegun, 2022), and efficiency and control strategies in air conditioning bear on the temperature stability that reagent storage and instrument calibration require (Sunday *et al*., 2019).

Asset integrity practice contributes a complementary perspective. Non-destructive testing approaches to integrity management establish the principle that inspection regimes should be risk-weighted rather than uniform (Atta *et al*., 2020), with method selection determined by the failure mode of concern (Atta *et al*., 2021), and with inspection standards and quality assurance practices defining what an acceptable condition assessment looks like (Atta *et al*., 2022). Translated into laboratory terms, this argues for differentiated maintenance intensity across the analyser fleet according to the consequence of each instrument's failure for turnaround.

Power supply is the second recurring constraint. Where grid supply is intermittent, load distribution across hybrid installations determines whether critical equipment runs continuously (Sunday and Omoegun, 2019), and integration of alternative generation is a practical intervention rather than a long-term aspiration (Sunday and Omoegun, 2018). Distribution network design, including grounding and protection arrangements, affects both continuity and equipment survival in emerging network conditions (Adeniji *et al*., 2020), voltage control becomes more complex where distributed generation is present (Oshevire *et al*., 2017), and emerging arrangements for local energy exchange indicate how facility-level supply may be organised in future (Shittu *et al*., 2021). None of this is laboratory science, but all of it determines whether the laboratory can run.

2.6. Workflow Optimization Interventions

The dominant methodology is Lean Six Sigma, usually operationalised through the Define, Measure, Analyze, Improve, Control cycle and supported by value stream mapping, Pareto analysis and root cause analysis. Lean contributes the identification and elimination of waste, particularly waiting, transportation, over-processing and defects; Six Sigma contributes variation reduction, which matters because TAT distributions are typically right-skewed and clinicians experience the tail rather than the median.

Reported interventions cluster into five types, set out in full as Domain B of the model below: demand and order management, specimen logistics, layout and flow redesign, automation and informatics, and post-analytical release.

A parallel literature on lean operations in resource-constrained organisations is directly relevant to laboratories that cannot fund a dedicated improvement infrastructure. Ambali *et al*. (2021) propose a lightweight adaptation of the DMAIC cycle for organisations without specialist quality staff, and related work demonstrates cycle time reduction in a service process using the same approach (Oyeleye *et al*., 2022). This literature is unusually explicit about enabling conditions. Standard operating procedures are treated not as documentation overhead but as strategic assets that carry process knowledge across staff turnover (Eyetsemitan *et al*., 2022). Governance alignment across stakeholders is identified as a precondition wherever a process crosses organisational boundaries (Eyetsemitan *et al*., 2020), as the total testing process invariably does, and external compliance requirements are translated into workflow terms rather than treated as constraints imposed from outside (Eyetsemitan *et al*., 2021).

The effect sizes reported for laboratory Lean interventions are substantial where reported individually, the reduction from 68 to 59 minutes and from 30 per cent to 3 per cent error documented by Inal *et al*. (2018) being the most fully specified example, but the literature does not permit direct comparison across settings, since Ambali *et al*. (2021) and Lokesh *et al*. (2020) describe comparable adaptations without reporting a common baseline or a common outcome metric. That absence of comparability is itself consistent with the operation of moderating factors that the workflow literature does not usually model.

2.7. Staff Competence, Training and Professional Development

The capacity literature approaches the same problem from the human side. SLMTA is the most extensively documented example in resource-limited settings. It is competency-based and task-oriented, delivered through a series of short workshops separated by intervals in which participants execute improvement projects in their own laboratories with supervisory or on-site mentorship, and evaluated using an audit checklist derived from ISO 15189 requirements (Yao *et al*., 2014b). Across 617 laboratories in 47 countries, baseline audit scores averaged 39 per cent with the large majority rated below one star, and implementation produced significant improvement (Yao *et al*., 2014a). The underlying curriculum design, built around prescribed management tasks and hands-on activity rather than lecture, is set out in the programme's original description (Yao *et al*., 2010).

Evaluations are notable for what they identify as success factors. Sisay *et al*. (2015), assessing outcomes in Addis Ababa, found that laboratories receiving adequate and timely mentorship were substantially more likely to score well, and that the leading contributors to failure were absence of customer satisfaction assessment, poor staff motivation and irregular equipment maintenance. Audu *et al*. (2014) report that Nigerian laboratories implementing SLMTA with expert on-site mentorship improved faster and more steadily than those without it. Sustainability has been addressed through country ownership, with programme functions embedded in ministry structures rather than sustained by external projects (Masamha *et al*., 2014), through training-of-trainers strategies that build national rather than facility-level capacity (Maruta *et al*., 2014), and through time-bounded initiatives designed to convert stalled improvement into completed accreditation (Ndegwa *et al*., 2022).

The education literature supplies the mechanisms behind these findings. Professional development, rather than initial qualification, is what determines competence in handling non-routine cases (Yeboah *et al*., 2019), and pedagogical strategy must be adapted to resource-constrained environments rather than transplanted from well-resourced ones (Bobga *et al*., 2018). Instruction supported by appropriate technology improves outcomes where it is integrated with the task rather than added to it (Boakye *et al*., 2020), a parallel that holds for laboratory training because both are skill-acquisition settings in which a tool positioned alongside the task, rather than embedded within it, adds cognitive load without improving transfer, and comparative curriculum analysis shows how differently structured programmes produce different competence profiles from similar inputs (Boakye *et al*., 2021). The use of progress data to individualise instruction is a direct analogue of competency-based laboratory training (Yeboah *et al*., 2022), as is the structured, documented development plan built around defined individual objectives (Yeboah and Oloto, 2022) and the compliance frameworks that specify what such planning must contain (Oloto and Yeboah, 2022). Collaboration between the training function and the environment in which the learner works is repeatedly found to condition transfer (Ogbona *et al*., 2020b), and career transition research shows how competence developed in one setting is or is not carried into another (Ogbona *et al*., 2020a). Where training is delivered through digital platforms, evidence-based design matters (Orise and Niniola, 2020), and real-time performance dashboards allow supervisors to observe competence developing rather than inferring it from attendance (Orise and Niniola, 2022).

2.8. Safety Management, Human Error and Process Discipline

A distinct literature addresses what happens between training and practice: whether procedures are actually followed under operational pressure. Because industrial safety management has studied this question for longer and more systematically than laboratory quality management, it is a useful source of mechanism. Human error causation frameworks distinguish error types by the conditions that produce them rather than by the individual who commits them (Obriki and Arumosoye, 2020), and work on the recurrence of unsafe behaviour identifies the feedback loops through which a workaround becomes normal practice (Obriki and Arumosoye, 2022). The parallel with laboratory procedure is close: the mechanisms that cause an operator to omit a check under time pressure are the same whether the omission is a safety violation or a skipped specimen identification step.

Several components of this literature map onto the model developed below. Near-miss and hazard observation reporting converts events that caused no harm into improvement data, which is precisely what a specimen rejection or a delayed validation is in TAT terms (Arumosoye and Obriki, 2019; Obogo *et al*., 2021a). Proactive hazard recognition depends on staff having both the competence to notice a problem and the authority to raise it (Obogo *et al*., 2019a), and management walkthrough frequency and coverage are linked to observable culture outcomes, which is an argument for structured supervisory presence rather than periodic audit alone (Obriki and Arumosoye, 2019). Organisational learning maturity models describe the progression from reactive correction to systematic prevention (Arumosoye and Obriki, 2021), and institutionalisation frameworks address the specific problem of making practices persist across projects and staff turnover (Obriki and Arumosoye, 2021).

The governance and audit strands are equally transferable. Internal audit systems for quality, health, safety and environment provide a template for the internal audit function that accreditation requires of laboratories (Obogo *et al*., 2020a), and safety governance models for large facility operations address accountability where multiple units share a process (Obogo *et al*., 2022). Governance-oriented models of performance in multi-contract environments speak to the accountability gap that appears when specimen transport is outsourced or shared with portering services (Arumosoye and Obriki, 2020; Obogo *et al*., 2021c). Data-driven risk control frameworks establish the measurement discipline on which any of this depends (Obriki and Arumosoye, 2018), and leadership-driven culture transformation is identified as the mechanism by which such systems are actually adopted (Obogo *et al*., 2019b).

Workforce safety training models are directly analogous to competency-based laboratory training, and the evidence that their effect depends on reinforcement rather than single exposure applies equally (Obriki *et al*., 2022a). Systematic hazard identification and risk control practice supplies the method for anticipating failure points in a redesigned workflow before deployment (Obogo *et al*., 2019c), and management system reviews in maintenance-intensive operations show how procedural systems degrade when workload rises (Obogo *et al*., 2020c). Risk pathway and risk management modelling for high-consequence operations demonstrate the value of tracing a hazard through its full sequence rather than assessing steps in isolation (Arumosoye and Obriki, 2022; Obogo *et al*., 2020b), and compliance systems research shows that documented conformance and actual practice diverge unless verification is built in (Obogo *et al*., 2021b). Environmental stressors such as heat are shown to degrade performance independently of competence, which matters in laboratories without reliable climate control (Arumosoye and Obriki, 2018), and emergency preparedness and evacuation planning is a continuity requirement for any facility holding time-critical work in progress (Obriki *et al*., 2022b).

Behavioural research in administrative settings reaches compatible conclusions. Awareness alone is a weak predictor of practice, and procedures that conflict with workload are bypassed rather than followed (Onche and Ogbonna, 2022; Onche *et al*., 2020). Taken together, these literatures support treating adherence as a distinct construct with its own determinants rather than as an automatic consequence of training.

2.9. Information Systems, Data Governance and Measurement

TAT cannot be managed without being measured, and measurement is an informatics problem before it is a management problem. The health system literature treats interoperability, data quality and analytics architecture as the backbone on which operational improvement depends (Ilodigwe and Adesemoye, 2021), and applied hospital studies show how real-time informatics reduces decision delay (Nnaji and Akinlolu, 2022). Business intelligence applied to resource allocation demonstrates how operational data supports staffing and capacity decisions (Owoade *et al*., 2022), and predictive approaches extend the same data from description to anticipation, whether in outbreak forecasting (Oparah *et al*., 2022), risk stratification for preparedness planning (Oparah *et al*., 2021a), or the scaling of remote monitoring services (Oparah *et al*., 2021b). Forecasting method developed for commercial demand estimation addresses the same statistical problem as forecasting daily specimen arrivals (Basnet *et al*., 2021), and resilient logistics frameworks combining prediction with localised distribution offer a template for specimen and consumable movement under disruption (Anene and Clement, 2022).

The systems on which this depends have their own literature. Availability and performance of shared enterprise platforms under high concurrency is a measurable design property rather than a matter of luck (Odejobi and Ahmed, 2018), and predictive resource scaling addresses the load variability that causes systems to slow at exactly the busiest moment (Ahmed *et al*., 2020). Architectural work on scalable and secure system design (Ahmed and Odejobi, 2018a), resource allocation modelling (Ahmed and Odejobi, 2018b; Ahmed *et al*., 2019) and database optimisation (Odejobi *et al*., 2019) addresses the responsiveness of the information system through which every timestamp passes. Identity and access management determines who can validate and release a result, and federated approaches matter where a laboratory serves multiple institutions (Oshoba *et al*., 2019; Ladapo *et al*., 2019). Migration practice is directly relevant to laboratories replacing legacy systems, an exercise that routinely degrades turnaround during transition (Ladapo *et al*., 2022b), as is the practice of assessing security-critical systems offline before deployment (Ladapo *et al*., 2018). Immutable audit trails for configuration change provide the assurance that reported timestamps have not been altered (Oshoba *et al*., 2020), disciplined release tooling reduces the defect rate in system changes (Badmus *et al*., 2020), a comparison that holds because both are configuration-managed environments in which an untested change released into production, whether a CRM workflow or a LIS auto-verification rule, propagates errors at the same speed it propagates the intended fix, and human-in-the-loop designs describe the division of labour between automated rules and human judgement that auto-verification requires (Ladapo *et al*., 2022a).

Because laboratory timestamps are clinical data, the measurement subsystem carries governance obligations. Legal and ethical risk modelling establishes the position from which those obligations are assessed (Mbonu *et al*., 2018), comparative regulatory analysis matters where systems are hosted across jurisdictions (Mbonu *et al*., 2019a), and data protection impact assessment provides the procedure for evaluating a proposed use of the data (Mbonu *et al*., 2022b). Identity and access governance controls who sees what (Mbonu *et al*., 2020a; Mbonu *et al*., 2022c), risk-based business intelligence architecture structures analytic use without exposing the underlying records (Mbonu *et al*., 2021a), and general controls frameworks describe how the integrity of a reporting system is assured and evidenced (Mbonu *et al*., 2022a). Log analytics and automated incident response detect and contain failures of the systems that carry the data (Mbonu *et al*., 2019b), infrastructure governance addresses the configuration drift that undermines them (Mbonu *et al*., 2020c), forensic analytics illustrates the evidentiary standard that audit data must meet (Mbonu *et al*., 2021c), and automated testing techniques bear on the reliability of the rule logic underlying auto-verification (Mbonu *et al*., 2021b; Borah *et al*., 2022). Digital transformation of supply operations with embedded controls shows how governance requirements are met without abandoning responsiveness (Mbonu *et al*., 2020b).

2.10. The Diagnostic Supply Chain and Procurement

A laboratory cannot report a result it lacks the reagent to produce, and consumable stock-outs recur throughout the root cause literature. Shortage early warning models convert a lagging indicator into an actionable forecast, which is the supply chain analogue of a TAT dashboard (Eze *et al*., 2022a), and readiness maturity models offer a staged improvement structure comparable to stepwise accreditation schemes (Eze *et al*., 2022b). Traceability and chain-of-custody frameworks establish provenance for materials entering the laboratory (Aneke and Adesemoye, 2019), risk-based decision-making structures the response when a deviation is found (Aneke and Adesemoye, 2020), and corrective and preventive action research asks whether such responses actually prevent recurrence (Aneke *et al*., 2022a), which is the same question this paper raises about the durability of improvement gains. Import and trade compliance models govern the border processes that often dominate lead time in import-dependent systems (Aneke and Adesemoye, 2021), and the consequences of quality failure for antimicrobial resistance illustrate what is at stake when inputs are unreliable (Aneke *et al*., 2022b), a concern that extends to the antimicrobial testing that laboratories themselves perform (Gbadamosi and Obogo, 2013). Last-mile distribution research addresses the specific problem of serving peripheral facilities from central stores (Asiedu and Asiedu, 2022), and interaction screening frameworks illustrate the clinical decision support that timely diagnostic and medication data are meant to enable (Asiedu, 2022).

Procurement practice determines whether these requirements are met in a particular hospital. Process automation improves procurement cycle time and transparency (Akinleye and Adeyoyin, 2021), supplier relationship management determines responsiveness when demand changes (Akinleye and Adeyoyin, 2022b), and negotiation optimisation addresses the cost side without which timeliness improvements are unaffordable (Akinleye and Adeyoyin, 2022a). Data-driven lean approaches to supply chain optimisation apply the same method used inside the laboratory to the chain that supplies it (Efobi *et al*., 2022b), analytic tooling makes cost and consumption visible at the level of the individual line item (Akin-Oluyomi *et al*., 2020), a comparison that holds because both settings face the same underlying problem, namely that high-volume transactional data becomes actionable only once it is aggregated and visualised at the line-item level rather than reviewed in raw form, and data-driven operations management frameworks address performance improvement in the institutional context (Efobi *et al*., 2021). Sustainable procurement criteria (Efobi *et al*., 2022a) and decision frameworks reconciling material safety with circularity objectives (Okojie and Abioye, 2020) extend the same logic to the environmental obligations laboratories are increasingly required to meet alongside timeliness.

2.11. The Clinical Interface and Health System Context

Because the first and last segments of the brain-to-brain loop belong to clinical rather than laboratory staff, clinical service delivery is part of the evidence base for TAT. Infection prevention and control compliance depends on the timely return of microbiology results, and stewardship decisions cannot be made until they arrive (Omaghomi *et al*., 2022). Integration of screening into routine primary care generates predictable diagnostic demand that laboratories must be resourced to absorb (Akinlolu *et al*., 2022), and real-time informatics is the mechanism by which the resulting information reaches the decision point without delay (Nnaji and Akinlolu, 2022).

Health system context conditions all of this. Financing and provider payment arrangements shape whether laboratories are resourced to meet timeliness expectations (Ilodigwe and Adesemoye, 2019a), delivery models determine where testing physically occurs and therefore how far specimens travel (Ilodigwe and Adesemoye, 2020), and the data architecture of the system determines whether performance can be observed at all (Ilodigwe and Adesemoye, 2021). The general finding that innovation does not improve outcomes without functioning delivery arrangements applies with particular force to diagnostics, where the product of the innovation is information that must reach a clinician in time to change a decision (Ilodigwe and Adesemoye, 2019b).

2.12. The Interaction between Process and People

Read together, these literatures suggest a reciprocal relationship that none of them models explicitly. Workflow redesign creates a demand for competence. A single-piece flow arrangement requires operators who can run multiple stations; auto-verification requires scientists who understand rule logic well enough to trust and to audit it; delegated validation requires judgement that must be trained and certified. Redesign without the matching competence produces either non-adoption or unsafe adoption.

Conversely, capacity building creates a demand for process latitude. Trained staff who identify a bottleneck but lack authority to alter transport schedules, reallocate stations or change validation rules experience the classic conditions for disengagement. The competence is real but its expression is blocked, and the observable result is that training evaluations record improvement at Kirkpatrick's learning level without corresponding improvement at the behaviour and results levels (Kirkpatrick, 1994).

This reciprocity explains a common practical observation: TAT gains achieved during an improvement project regress within months of its conclusion. Where the gain rested on redesign alone, it decays as staff turnover removes the individuals who absorbed the new routine informally, which is the argument for treating standard operating procedures as durable assets rather than compliance artefacts (Eyetsemitan *et al*., 2022). Where it rested on training alone, it decays as trained individuals encounter structural obstacles and revert to the path of least resistance, the pattern documented wherever procedural adherence has been observed under workload pressure (Obriki and Arumosoye, 2022).

Taken together, these literatures leave four things unresolved. No widely used framework specifies workflow and capacity as co-equal, interacting levers acting on a shared set of TAT outcomes. The moderating role of structural conditions, including facility design, equipment reliability, power supply, information system availability, consumable supply and staffing ratios, is acknowledged across separate literatures but rarely modelled together. Sustainability mechanisms are underspecified: studies report what was done and what changed, but seldom what maintained the change. And measurement is fragmented, with laboratories reporting incommensurable TAT definitions that prevent both benchmarking and the accumulation of comparable evidence. The model set out below is directed at these four points.

3. Model Development

3.1. Theoretical Foundations

The IWCO model draws on five bodies of theory, each contributing a distinct element.

3.2. Structure, Process and Outcome

Donabedian (1988) proposed that quality of care be assessed through the relationship between structure (the stable attributes of the setting), process (what is done) and outcome (what results). The framework supplies the model's basic architecture: TAT is a process-derived outcome; workflow and capacity interventions act on process; and the structural domain constrains what process change is achievable. Donabedian's insistence that structure enables but does not guarantee good process is exactly the logic needed to explain why laboratories with comparable equipment achieve very different turnaround times.

3.3. Lean Thinking and the Theory of Constraints

Lean thinking supplies the concepts of value, value stream, flow, pull and perfection (Womack and Jones, 1996), and the associated taxonomy of waste that has been applied extensively to laboratory processes. The theory of constraints (Goldratt and Cox, 1984) supplies a complementary and, for TAT, decisive insight: system throughput is governed by its single binding constraint, so improvement effort applied elsewhere yields no system-level gain. In TAT terms, accelerating analysis in a laboratory whose binding constraint is specimen transport will not reduce total TAT. The model therefore includes constraint identification as a mandatory step preceding intervention design.

3.4. Socio-technical Systems Theory

Socio-technical systems theory holds that the technical and social subsystems of an organisation are jointly optimised or not optimised at all, and that technical redesign undertaken without regard to the social system tends to produce worse outcomes than the arrangement it replaced (Trist and Bamforth, 1951). This is the theoretical warrant for the model's central claim that workflow and capacity are interdependent rather than additive, and it is supported empirically by the safety literature's finding that procedural systems fail at the point of adoption rather than the point of design (Obriki and Arumosoye, 2021).

3.5. Human Capital Theory and Absorptive Capacity

Human capital theory (Becker, 1964) treats training as investment and distinguishes general from firm-specific capital. General technical competence is portable, whereas competence in a particular laboratory's redesigned workflow is specific capital whose returns are lost on turnover, which implies that retention and documentation are components of capacity building rather than adjuncts to it. Cohen and Levinthal's (1990) absorptive capacity explains why two laboratories given identical guidance derive different benefit: the one with a stronger prior stock of relevant knowledge assimilates and applies it more effectively. The mechanism runs as a specific chain: capacity building enlarges a laboratory's stock of prior relevant knowledge; a larger stock allows staff to interpret value-stream and workload data faster and more accurately; more accurate interpretation targets workflow redesign at the true binding constraint rather than a plausible-looking one; and better-targeted redesign yields a larger realised TAT gain per unit of intervention effort.

3.6. Training Evaluation

Kirkpatrick's (1994) four levels of reaction, learning, behaviour and results provide the model's evaluation logic for the capacity lever, and guard against the common error of treating training attendance or post-test scores as evidence of operational improvement. Performance dashboards developed for professional training offer a practical means of observing the behaviour level directly rather than inferring it (Orise and Niniola, 2022).

Combining these, the model asserts: structural conditions set the feasible range of process performance; within that range, the binding constraint determines where improvement effort produces system-level gain; workflow redesign and capacity building must be jointly optimised because each creates the conditions under which the other is effective; the durability of any gain depends on process-specific human capital, which is vulnerable to turnover and must be protected through documentation, mentorship and retention; and improvement can only be directed and sustained where a measurement subsystem returns phase-specific, timely feedback to the people doing the work.

3.7. Approach to Model Development

This is a conceptual paper, and its method is theory synthesis rather than empirical testing.

Design: The study follows a narrative synthesis approach to model building, in which concepts are extracted from a purposively assembled body of literature, defined as constructs, and assembled into a framework whose relationships are stated as propositions.

Literature identification: Sources were identified through database searching using combinations of the terms turnaround time, total testing process, clinical laboratory, Lean, Six Sigma, workflow, laboratory infrastructure, predictive maintenance, safety management, health informatics, data governance, diagnostic supply chain, capacity building, competency-based training, mentorship and quality management system, supplemented by citation tracking from key reviews and by the grey literature of laboratory quality programmes. Priority was given to phase-wise TAT studies, intervention studies reporting TAT outcomes, evaluations of laboratory capacity programmes, and studies conducted in resource-constrained settings. Where the laboratory literature was thin on a determinant, adjacent literatures addressing the same mechanism were admitted, and the basis of the analogy is stated at the point of use.

Concept extraction and model assembly: Each source was read to extract reported determinants, intervention components, moderators and outcome measures. Items were grouped inductively into candidate constructs, retained where they appeared in more than one source and could be operationally defined, and then arranged according to the structure-process-outcome architecture, with interaction paths added where the literature supplied a mechanism rather than a correlation. Propositions were written to state each relationship in falsifiable form.

Validation strategy: The model presented here has face validity derived from its evidential base but has not been empirically validated. A validation programme is outlined in Section 4.6, comprising expert review by laboratory scientists and quality managers using a modified Delphi procedure, instrument development for the seventeen constructs, and testing in a multi-site interrupted time series or stepped-wedge design.

3.7. The Integrated Workflow and Capacity Optimisation (IWCO) Model

Overview

The model comprises six domains: structural inputs and contextual moderators (A), the two intervention levers (B and C), the integrating mechanisms through which those levers act on each other (D), the measurement and feedback subsystem that closes the loop (E), and the outcome hierarchy (F). The architecture is presented in Figure 1.

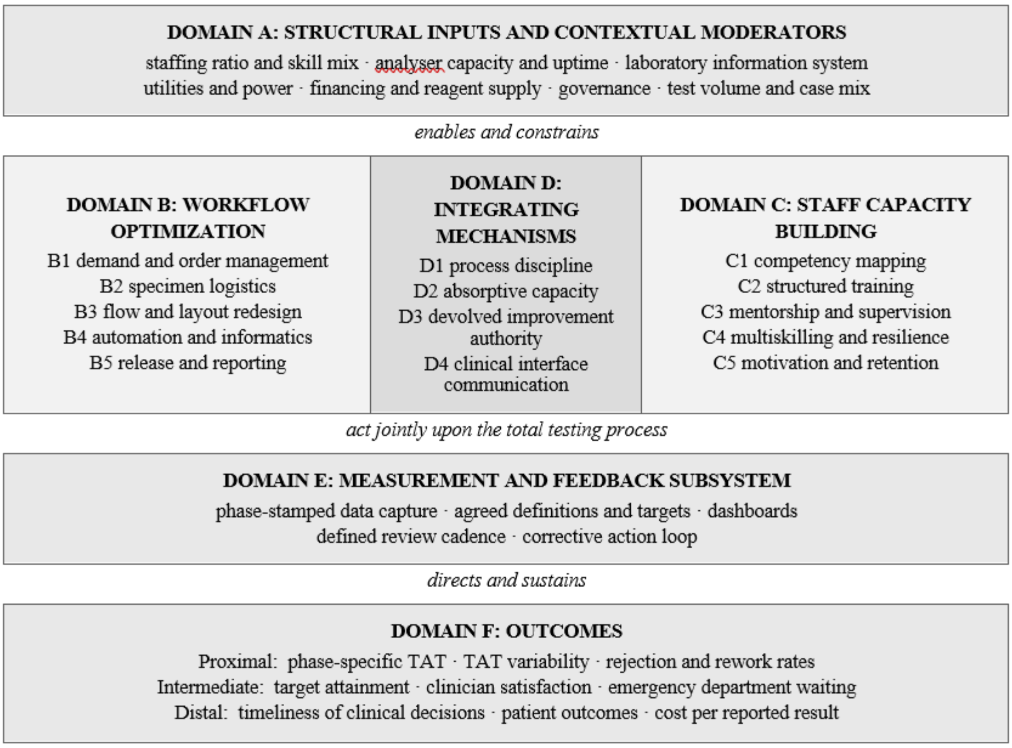

Fig 1: Schematic of the Integrated Workflow and Capacity Optimisation (IWCO) model.

3.8. Domain A: Structural Inputs and Contextual Moderators

Structural inputs are the relatively stable attributes of the laboratory and its host institution. Seven are specified: staffing establishment and skill mix relative to workload; analyser capacity, age and maintenance status (Sunday *et al*., 2020); laboratory information system presence, reliability and degree of integration with clinical systems (Odejobi and Ahmed, 2018); utilities, particularly electrical supply continuity and water (Sunday and Omoegun, 2019); financing and consumable supply reliability (Eze *et al*., 2022a); governance, including management commitment and the laboratory's standing within the institution (Obogo *et al*., 2022); and test volume with its case mix and temporal distribution.

These are modelled as moderators rather than as direct causes. A laboratory with three hours of daily power interruption has a ceiling on achievable TAT that no amount of flow redesign will lift, and the model's practical value lies partly in forcing that ceiling to be made explicit before improvement targets are set. Facility design decisions taken years earlier set a further ceiling on what physical rearrangement can achieve (Ogbete *et al*., 2018; Nwafor *et al*., 2019b).

3.9. Domain B: The Workflow Optimization Lever

B1. Demand and order management: Rationalising the test menu, deploying condition-specific order sets, applying minimum retest intervals, and distinguishing genuinely urgent from routine requests. The mechanism is reduction in the volume and irregularity of demand presented to fixed capacity, supported where possible by forecasting expected demand rather than reacting to realised demand (Basnet *et al*., 2021), both being demand-forecasting problems with a similar seasonality and noise structure, since audience arrivals and specimen arrivals each follow predictable daily and weekly cycles overlaid with irregular spikes.

B2. Specimen logistics: Rescheduling phlebotomy to flatten the arrival peak, fixed-interval transport rounds with defined maximum holding times, point-of-collection labelling, and acceptance and rejection criteria communicated to wards. The mechanism is reduction of waiting and transport waste, the largest single contributor to total TAT, and the design problem is the one addressed in last-mile distribution and resilient logistics research (Asiedu and Asiedu, 2022; Anene and Clement, 2022).

B3. Flow and layout redesign: Value stream mapping of the current state, identification of the binding constraint, reduction of batch size toward single-piece flow, physical rearrangement to eliminate movement, and levelling of work across the shift. The mechanism is reduction of queueing and non-value-adding motion, and the achievable extent of rearrangement is set by the spatial design of the facility (Ogbete *et al*., 2018).

B4. Automation and informatics: Barcode accessioning, analyser interfacing, auto-verification within defined limits, and real-time phase-stamped visibility. The mechanism is elimination of manual transcription and of waiting inherent in handoffs. The division of labour between automated rules and human judgement should be designed explicitly (Ladapo *et al*., 2022a), and changes validated before deployment, since automation staff do not trust is bypassed (Ladapo *et al*., 2018).

B5. Release and reporting: Delegated validation authority with defined competency criteria, structured critical result notification with closed-loop acknowledgement, and result presentation designed for rapid clinical uptake. The mechanism is compression of the post-analytical and post-post-analytical segments, which are commonly neglected because they are invisible in intra-laboratory metrics. Who may release what is an access control decision as much as a competency decision (Oshoba *et al*., 2019).

3.10. Domain C: The Staff Capacity Building Lever

C1. Competency mapping and gap analysis: Definition of the competencies each role requires across the whole total testing process, including boundary-spanning competencies, and structured assessment of individual and collective gaps against that definition. This is the analogue of value stream mapping on the human side and precedes any training investment (Yeboah and Oloto, 2022).

C2. Structured, competency-based training: Short, task-oriented instruction tied to defined competencies, delivered in cycles separated by intervals of applied practice rather than as one-off events, and evaluated against Kirkpatrick's behaviour and results levels rather than reaction and learning alone. Instruction should be integrated with the task rather than added to it (Boakye *et al*., 2020), individualised using progress data where possible (Yeboah *et al*., 2022), and reinforced rather than delivered once (Obriki *et al*., 2022a).

C3. Mentorship and supportive supervision: Regular on-site or supervisory mentoring during the interval between instruction and consolidation. The evidence identifies this as the component most strongly associated with programme success and the one most often curtailed under resource pressure (Sisay *et al*., 2015; Audu *et al*., 2014), and the frequency and coverage of supervisory presence is itself a measurable determinant of practice (Obriki and Arumosoye, 2019).

C4. Multiskilling and workload resilience: Cross-training so that stations can be covered across shifts and absences, rostering aligned to the demand profile produced by B2, and defined escalation procedures for surge conditions. This converts individual competence into system resilience, and it requires an establishment adequate to release staff for training in the first place.

C5. Motivation, ownership and retention: Recognition, participation in improvement decisions, transparent performance feedback, and attention to the conditions that drive attrition. This construct protects the process-specific human capital on which sustained gains depend, and leadership behaviour is the mechanism through which it is either built or eroded (Obogo *et al*., 2019b).

3.11. Domain D: Integrating Mechanisms

Domain D contains the model's distinctive theoretical content: four mechanisms through which the levers act on each other.

D1. Process discipline: The extent to which a redesigned workflow is executed as designed when unsupervised. Discipline is produced jointly by clear process design (Domain B) and by competence, ownership and supervision (Domain C). Neither lever generates it alone. Process discipline mediates the relationship between workflow redesign and TAT: a redesign with low discipline yields little of its theoretical benefit, the pattern documented wherever adherence has been measured against workload pressure (Obriki and Arumosoye, 2020; Onche and Ogbonna, 2022).

D2. Absorptive capacity: The laboratory's ability to convert improvement knowledge into applied practice. Capacity building raises absorptive capacity, which in turn raises the return on any given workflow intervention. This mechanism predicts that identical workflow interventions will yield larger TAT reductions in laboratories with prior capacity investment, and it corresponds to the progression described in organisational learning maturity models (Arumosoye and Obriki, 2021).

D3. Devolved improvement authority: The degree to which frontline staff may alter their own processes within defined limits. Authority is the channel through which capacity converts into workflow change; without it, trained staff cannot act on what they identify. This mechanism carries the model's explanation for training programmes that produce learning without results, and it is the condition under which proactive hazard and problem reporting actually occurs (Obogo *et al*., 2019a; Arumosoye and Obriki, 2019).

D4. Clinical interface communication: Structured, routine communication between laboratory and clinical units regarding TAT expectations, specimen quality, urgent request criteria and result acknowledgement. D4 mediates the interaction between the two levers directly rather than by co-location alone: communication quality determines whether a workflow change made under Domain B, such as a revised critical-result notification protocol, actually reaches clinical practice under Domain C as intended, or is instead implemented correctly inside the laboratory yet ignored, misread or worked around by clinical users, in which case the redesign records a process metric without the corresponding TAT gain. Because the first and last segments of the loop lie outside the laboratory, no purely internal intervention can compress them. Accountability across a shared process must be explicitly assigned rather than assumed (Arumosoye and Obriki, 2020), and the competencies involved are those of coordination across professional boundaries (Lilian *et al*., 2020).

3.12. Domain E: Measurement and Feedback

The measurement subsystem requires four elements: phase-level timestamps captured automatically at order entry, collection, receipt, accessioning, result generation, validation, release and acknowledgement; agreed TAT definitions and targets set with users, as required by ISO 15189 (International Organization for Standardization, 2012); visible reporting of median and 90th percentile TAT by phase, test and shift, since the tail rather than the median drives clinician perception; and a defined review cadence at which the data are examined by the staff who own the process and corrective action is assigned.

Design guidance comes from adjacent fields: analytics-driven performance models supply the logic that turns a display into an intervention (Nnaji and Akinlolu, 2022), business intelligence practice the link to resource allocation (Owoade *et al*., 2022), and data-driven risk control frameworks the discipline of measuring before acting (Obriki and Arumosoye, 2018). The system carrying the data must be reliable under load (Ahmed *et al*., 2020) and its configuration changes auditable (Oshoba *et al*., 2020). Because the underlying records are clinical, the subsystem sits within the same governance perimeter as any other health data platform, with defined legal and ethical positions (Mbonu *et al*., 2018), impact assessment before new analytic uses (Mbonu *et al*., 2022b), access governance (Mbonu *et al*., 2022c), general controls over reporting integrity (Mbonu *et al*., 2022a), and monitoring for failures of the platform itself (Mbonu *et al*., 2019b).

Feedback is modelled as a loop rather than as an output because it conditions both levers. Without phase-level data the binding constraint cannot be located, so workflow effort is misdirected; and without visible performance data, the awareness and ownership components of the capacity lever have nothing to attach to. The finding that a substantial minority of laboratory staff cannot correctly define TAT or name factors affecting it (Gebreyes *et al*., 2020) indicates how often this loop is absent.

3.13. Domain F: Outcomes

Outcomes are specified at three levels.

Proximal: phase-specific median and 90th percentile TAT; TAT variability; proportion of results within target; specimen rejection and rework rates; unplanned analyser downtime.

Intermediate: target attainment for stat and routine categories; clinician satisfaction with laboratory service; emergency department length of stay attributable to laboratory waiting; duplicate test ordering rate.

Distal: timeliness of clinical decisions; patient outcome measures in time-sensitive conditions; cost per reported result; accreditation status.

Distinguishing these levels matters because most published TAT interventions report only proximal outcomes; the model makes the missing links explicit as a research agenda rather than an assumption. The distal level is where health system value is realised (Ilodigwe and Adesemoye, 2019b).

3.14. Propositions

P1. Non-analytical phases account for the majority of total diagnostic TAT, as established in Section 2.3; therefore interventions targeting the analytical phase alone will produce limited reduction in total TAT.

P2. Workflow optimization reduces TAT only to the extent that it acts on the binding constraint; interventions applied to non-constraint steps will improve local metrics without improving total TAT.

P3. The effect of workflow optimization on TAT is mediated by process discipline (D1), which is itself a joint function of design clarity and staff competence, ownership and supervision.

P4. The effect of staff capacity building on TAT is mediated by devolved improvement authority (D3); in its absence, capacity building will produce gains at Kirkpatrick's learning level without corresponding gains at the behaviour and results levels.

P5. Workflow optimization and staff capacity building interact positively: the TAT reduction from both levers implemented together exceeds the sum of the reductions from each implemented alone.

P6. The durability of TAT gains is a function of process-specific human capital, and is therefore negatively associated with staff turnover and positively associated with documentation quality, mentorship intensity and retention.

P7. Structural conditions (Domain A), including facility design, equipment reliability, utility continuity and consumable availability, moderate the relationship between both levers and TAT, imposing a performance ceiling that no process or capacity intervention can exceed.

P8. In the absence of a functioning phase-level measurement and feedback subsystem (Domain E), gains from either lever will regress toward baseline within a defined post-intervention period.

3.15. Operationalisation and Implementation Constructs and Indicators

Table 2 sets out a suggested indicator and data source for each construct, providing the basis for instrument development and for empirical testing of the propositions.

Table 2: Constructs, indicators and data sources for the IWCO model.

Construct	Suggested indicator	Data source
Structural adequacy (A)	Staff-to-workload ratio; analyser uptime; hours of power interruption per week; reagent stock-out days; LIS unplanned downtime hours per month; documented TAT policy reviewed within the past 12 months (Y/N); proportion of urgent/STAT orders by service line	Establishment records, maintenance log, utilities log, store records; LIS administration log; governance/quality committee minutes; LIS order data by service line
Demand management (B1)	Duplicate order rate; proportion of requests marked urgent	LIS order data
Specimen logistics (B2)	Collection-to-receipt interval; coefficient of variation of hourly arrivals; rejection rate	LIS timestamps
Flow redesign (B3)	Mean batch size; receipt-to-accession interval; number of handoffs in the value stream	Process observation, value stream map
Automation and informatics (B4)	Proportion of results auto-verified; proportion of orders entered electronically	LIS configuration and audit data
Release and reporting (B5)	Validation-to-release interval; critical result acknowledgement rate and time	LIS, notification log
Competency coverage (C1, C2)	Proportion of staff assessed competent per defined competency, by role	Competency assessment records
Mentorship intensity (C3)	Mentorship hours per laboratory per quarter	Supervision records

Multiskilling (C4)	Mean number of stations each staff member is certified for	Competency matrix
Motivation and retention (C5)	Annual turnover rate; staff engagement score	Human resource records, staff survey
Process discipline (D1)	Audit-observed adherence to standard operating procedures	Internal audit
Absorptive capacity (D2)	Proportion of improvement ideas implemented per capacity-hour invested	Training/mentorship records cross-referenced with improvement log
Devolved authority (D3)	Number of staff-initiated process changes implemented per period	Improvement log
Clinical interface communication (D4)	Documented clinician-laboratory service reviews per quarter	Meeting minutes; service review records
Measurement functionality (E)	Proportion of episodes with complete phase timestamps; review meeting frequency	LIS completeness audit, meeting minutes
TAT outcomes (F)	Median and 90th percentile TAT by phase and test; proportion within target	LIS

3.16. Implementation Sequence

The model is operationalised through five phases over an indicative twelve to eighteen months, mirroring the cycle length that competency-based laboratory programmes have found effective.

Phase 1: Diagnose (months 1 to 2): Establish or repair phase-level timestamping. Measure baseline TAT by phase, test and shift, reporting median and 90th percentile. Conduct value stream mapping and identify the binding constraint. Conduct competency mapping and gap analysis. Document structural ceilings honestly, including equipment, utility and consumable constraints, using systematic identification of failure points rather than impression (Obogo *et al*., 2019c). Agree TAT targets with clinical users.

Phase 2: Design (months 2 to 4): Design workflow changes targeted at the identified constraint, and design the training and mentorship plan targeted at the identified competency gaps, with the two designed together so that each redesigned step has an identified competent owner. Define the devolved authority envelope: which changes frontline staff may make without escalation. Trace each proposed change through its full sequence before deployment rather than assessing steps in isolation (Arumosoye and Obriki, 2022).

Phase 3: Deploy (months 4 to 9): Implement in paired increments, each consisting of a workflow change and its supporting competency development, rather than as a workflow project followed later by a training project. Sequence increments by expected constraint relief. Maintain mentorship at planned intensity, protecting it from the resource pressure that typically erodes it first.

Phase 4: Drive (months 9 to 12): Institute the review cadence. Publish dashboards visible to laboratory and clinical staff. Assign and track corrective actions, verifying that they prevent recurrence rather than merely closing the incident (Aneke *et al*., 2022a), and use near-miss events such as rejected specimens and late validations as improvement data rather than as exceptions (Obogo *et al*., 2021a). Re-identify the binding constraint, which will have moved, and begin the next increment.

Phase 5: Sustain (month 12 onward): Convert redesigned workflows into documented standard operating procedures and induction curricula so that process-specific capital survives turnover (Eyetsemitan *et al*., 2022). Embed competency reassessment on a defined cycle. Verify conformance rather than assuming it, since documented practice and actual practice diverge without checking (Obogo *et al*., 2021b). Monitor for regression and treat regression as a signal about Domain E rather than about individual performance.

4. Discussion and Conclusion

4.1. Theoretical Implications

The model's central theoretical claim is that workflow and capacity are not additive inputs to TAT but interacting ones, and that the interaction runs through identifiable mechanisms rather than being a general assertion of complementarity. This reframes several puzzles in the literature. The variable effect sizes reported for similar Lean interventions become explicable as variation in absorptive capacity and process discipline. The gap between strong learning outcomes and weak operational outcomes in training evaluations becomes explicable as a devolved authority problem. The widely observed post-project regression becomes explicable as depletion of process-specific human capital in the absence of documentation and feedback.

The model also relocates the unit of analysis. Because the first and last segments of the loop belong to clinical rather than laboratory staff, a model confined to the laboratory addresses at most the middle of the problem; Domain D4 is the acknowledgement that improvement effort must cross the organisational boundary.

4.2. Implications for Practice

Three practical implications follow: measure by phase before designing, since the binding constraint is otherwise unknown; pair every workflow change with its competency requirement in the same increment rather than running process and training initiatives on separate timelines; and treat mentorship and retention as core components rather than soft extras, since the evidence identifies them as the strongest correlates of sustained improvement.

4.3. Implications for Policy

For health system planners and accrediting bodies, the model suggests that TAT requirements should be accompanied by requirements for the measurement infrastructure that makes them meaningful, since a laboratory that reports only intra-laboratory TAT can comply while its users continue to experience delay. It also suggests that investment in analysers without matched investment in transport, information systems, utilities, consumable supply and staffing will yield disappointing returns, because the analytical phase is rarely the binding constraint. This is the operational form of a broader finding: capital investment produces outcomes only where the delivery arrangements surrounding it are functional (Ilodigwe and Adesemoye, 2019b).

4.4. Relevance to Resource-Constrained Settings

The first phase requires measurement and analysis rather than capital. Where automation is unaffordable, Domains B1 to

B3, the whole of Domain C, and Domains D and E remain fully actionable, and the pre-analytical evidence suggests the largest available gains lie there. Lightweight adaptations of Lean Six Sigma for organisations without dedicated quality staff apply directly (Ambali *et al*., 2021), as do infrastructure models designed for constrained systems rather than transplanted from high-income ones (Aminu-Ibrahim *et al*., 2018; Aminu-Ibrahim *et al*., 2020). Documenting structural ceilings honestly also guards against setting targets staff cannot meet, itself a driver of the demotivation the model treats as a cause of failure.

That the first phase does not require capital does not mean it is free. The five-phase cycle draws repeatedly on the time of exactly the staff a small, resource-constrained laboratory can least spare: value-stream mapping and competency mapping in Phase 1, joint design work in Phase 2, mentorship maintained at planned intensity through Phase 3, and dashboard review in Phase 4 all require senior scientist or pathologist time that is not backfilled by any capital substitute. In a very small laboratory this staff-time budget, not capital, is plausibly the tighter constraint on adoption. Minimising it argues for phasing the model rather than deploying it in full: a first pass confined to Phase 1 diagnostic work and a single paired increment in Phase 3, run by a visiting mentor with minimal ongoing demand on local staff, before the full five-phase cycle and its larger time commitment are attempted.

4.5. Equity Implications

Turnaround time is unequally distributed within and between health systems, and improvement effort can widen as well as narrow that gap. Peripheral and rural facilities experience longer pre-analytical intervals because of transport distance, so interventions confined to central laboratories improve the metric for patients who were already best served (Aminu-Ibrahim *et al*., 2020). Delivery models that move testing closer to the patient change where the clinical decision is made and therefore reshape rather than remove the communication problem (Ilodigwe and Adesemoye, 2020; Oparah *et al*., 2021b), and financing arrangements determine which facilities can afford the measurement and staffing the model requires (Ilodigwe and Adesemoye, 2019a).

The model carries a further, self-generated equity risk that follows directly from its own architecture rather than from geography. Absorptive capacity (D2) and the Diagnose and Design phases of the implementation sequence both require staff time and a baseline of prior competence before they can be run at all. The facilities with the weakest baseline capacity are, by definition, the model's intended beneficiaries, but they are also the facilities least able to release senior staff for value-stream mapping, competency mapping and design work without disrupting service. Implemented as specified, the model therefore risks widening the gap it is meant to close, with better-resourced facilities completing the cycle and realising its gains while the weakest facilities cannot begin it. Mitigating this requires deliberate design rather than an assumption of uniform uptake: pooled or regional mentorship capacity that can be deployed to a weak facility rather than requiring that facility to supply its own, and a minimal-effort entry point, such as a short, mentor-led diagnostic phase requiring only a few days of staff time, that lets the weakest facilities begin the cycle before they can resource the full five-phase sequence.

4.6. Limitations and Further Work

Four limitations should be stated. First, the model is conceptual and unvalidated; its propositions are derived from synthesis, not from testing. Second, the underlying literature is heterogeneous in TAT definition, setting and design, and is subject to publication bias favouring successful interventions. It also draws on adjacent fields, particularly safety management, maintenance engineering and information systems, whose transferability to laboratory operations is argued rather than demonstrated; those arguments are stated at the point of use so that readers can judge them individually. Third, the model does not quantify the relative weight of its constructs, so it guides where to look rather than how much to expect. Fourth, disciplines with fundamentally different process architectures, particularly anatomic pathology and microbiology with their long biological or preparation-dependent intervals, may require adaptation of the phase structure.

Four directions for further work follow. A modified Delphi study with laboratory scientists, pathologists and quality managers would establish content validity and refine the construct set. Instrument development would produce measures for the seventeen constructs, particularly the Domain D mechanisms, which are the least well operationalised. A multi-site stepped-wedge or interrupted time series design comparing workflow-only, capacity-only and integrated arms would test Proposition 5 directly, which is the core empirical claim. Any such test must also rule out a specific alternative explanation for apparent super-additivity: TAT is bounded below by an analytical and physical floor, and combined-lever interventions are often deployed first in the worst-performing laboratories, so the combined arm could show the largest gain through regression toward that floor rather than through genuine interaction between the levers. A rigorous test therefore requires allocation of laboratories to arms that is randomised or matched rather than driven by observed baseline performance, together with a pre-specified floor term in the statistical model so that convergence on a physical limit is not mistaken for interaction. And longitudinal follow-up beyond twelve months post-intervention would test Propositions 6 and 8, on which the practical value of the sustainability components rests.

4.7. Conclusion

Diagnostic turnaround time has remained a stubborn problem not because effective interventions are unknown but because they are applied in isolation from one another. The workflow tradition has shown that redesign reduces delay; the capacity tradition has shown that competency-based training with mentorship transforms laboratory performance; the infrastructure, reliability, informatics and supply chain literatures have each shown they can impose a ceiling on what either achieves. What none has articulated is the dependence of each on the other. The Integrated Workflow and Capacity Optimisation model specifies that dependence through four mechanisms, situates both levers within a structural context that bounds them, and makes measurement and feedback a constitutive element rather than an afterthought. Its eight propositions are offered for testing, and its five-phase sequence as a starting point for laboratories that must reduce turnaround time using the resources they already have.

Declarations

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