Development of a Turnaround Time Dashboard for Blood Tests

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Abstract

Turnaround time (TAT) is a critical performance indicator in laboratory medicine, directly influencing clinical decision-making and patient outcomes. Delays in reporting can compromise timely treatment, particularly for urgent or life-threatening conditions where rapid laboratory results are essential. Despite this importance, most laboratories monitor TAT retrospectively and primarily through median values, offering limited insight into workflow inefficiencies. This study developed and evaluated a business intelligence dashboard for real-time and retrospective TAT monitoring, aligning with digital health initiatives that leverage data-driven tools to enhance healthcare quality and patient safety.

Data extracted from the Laboratory Information System (LIS) was transformed into key performance indicators, including median TAT, compliance with thresholds, and phase-specific data. Semi-structured interviews with laboratory managers informed indicator selection and guided user-centred dashboard design. Usability testing with laboratory staff assessed clarity, relevance, and ease of use.

By transforming raw LIS data into actionable insights, the dashboard demonstrated potential to reduce diagnostic delays, ensure more timely reporting of critical results, and strengthen clinical decision-making, thereby supporting improved patient outcomes. Future work should expand the range of indicators, test scalability across diverse laboratory contexts, and explore predictive analytics to enable early intervention in potential delays.

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Abbreviations

aTAT	Analytical Turnaround Time
AI	Artificial Intelligence
BI	Business Intelligence
CSV	Comma-Separated Values
DAX	Data Analysis Expressions
EHR	Electronic Health Record
FREC	Faculty Research Ethics Committee
GDPR	General Data Protection Regulation
GUI	Graphical User Interface
iCM	iSOFT Clinical Manager
KPI	Key Performance Indicator
LIS	Laboratory Information System
MDH	Mater Dei Hospital
ML	Machine Learning
PCR	Polymerase Chain Reaction
PDF	Portable Document Format
QI	Quality Indicator
RIS	Radiology Information System
RNA	Ribonucleic Acid
RYG	Red-Yellow-Green
SARS-CoV-2	Severe Acute Respiratory Syndrome Coronavirus 2
SLA	Service-Level Agreement
STAT	Statim (urgent test request)
SQL	Structured Query Language
SUS	System Usability Scale
TAT	Turnaround Time
TTP	Total Testing Process
URECA	University of Malta Research Ethics Committee Assessment

1. Introduction

1.1 Motivation of Research

The efficiency of a hospital's clinical laboratory is essential for the delivery of high-quality healthcare, particularly in acute and emergency care settings. One of the most critical performance metrics for laboratory operations is Turnaround Time (TAT), which represents the time from when a sample is collected to when the test results are made available to clinicians. A fast and consistent TAT is essential for timely diagnosis and treatment, reducing patient wait times, facilitating quicker decision-making for clinicians, and ultimately improving patient outcomes. Delays in TAT can lead to prolonged emergency department length of stay stays, treatment delays, and reduced patient satisfaction, highlighting the importance of monitoring and managing this metric efficiently [1, 2].

Currently at Mater Dei Hospital laboratories, TAT is calculated retrospectively using data extracted from the Laboratory Information System (LIS) monthly. This data is used to generate static reports that provide a snapshot of past performance. This approach has several limitations, mainly because there is a lack of real-time data monitoring, making it difficult to identify and address operational inefficiencies at the opportune time as they occur. Reports and insights generated through historical data have limited flexibility and are unable to provide in-depth, actionable insights for specific areas or test types without further manual analysis. Consequently, TAT issues are often addressed by laboratory management after these have already caused a delay in patient care. Static reports usually report only the mean TAT for that period, and since TAT data has a positive skewness, reporting of TAT mean masks good performance and conceals poor efficiency [3].

Mater Dei Hospital's pathology laboratories process approximately 13 million tests annually across all blood science laboratories, with the biggest contributor being the Clinical Chemistry section having a test portfolio of over 100 tests. Tests can be requested with two priorities, routine and urgent, with 20 % of tests ordered in 2024 being requested as urgent, mainly originating

from the Emergency Department and Intensive Care Unit. Routine workload peaks between 10am and 1pm, creating bottlenecks that frequently affect the TAT of priority samples [4]. This growing workload and high share of urgent testing underscore the operational pressures faced by laboratories reinforcing the need for continuous TAT monitoring.

The development of a Turnaround Time Dashboard will address these challenges by offering an interactive platform where key performance indicators can be tracked continuously. This tool will allow laboratory staff to monitor real-time TAT for high-priority tests whilst also identifying process inefficiencies and bottlenecks as they emerge.

The proposed solution will integrate real-time data from the LIS, clean, process data, and display the results in an easy-to-understand visualisation via Power BI. This will provide a powerful tool for laboratory managers and clinicians to assess current performance, forecast delays, and take corrective actions. Periodical reports could also be generated using this tool for statistical recording. By offering customizable filters, users can drill down into specific test types, laboratory sections, or periods, making it a flexible and responsive tool for continuous quality improvement in laboratory services.

This tool can have an impact on the operational efficiency of hospital laboratories whilst improving patient care by reducing delays in test result reporting and facilitating quicker clinical decision-making [5, 6].

1.2 Problem Definition

Despite its importance, current TAT monitoring at Mater Dei Hospital laboratories relies on monthly retrospective reports, generated from LIS data. This approach provides only static summaries of past performance, where process delays are often identified only after they have already affected patient care, limiting the opportunity for timely intervention.

Existing reporting methods are also inflexible, requiring manual effort to extract detailed insights by test type, section, or workload. These limitations highlight a gap between the large volume of data already available in the LIS

and its translation into actionable, real-time intelligence for quality improvement.

The problem addressed in this study is therefore the lack of a dynamic and user-centred system for monitoring laboratory TAT. Without such a tool, laboratories remain constrained to retrospective assessments that obscure inefficiencies, delay corrective action, and reduce the capacity to optimise patient care through timely reporting of results.

1.3 Aim

To develop a real-time, interactive TAT dashboard that allows the dynamic monitoring of turnaround times. Automating data extraction and visualisation, will enable faster identification of delays, improve workflow efficiency, and provide insights that enhance patient care.

1.4 Objectives

- Acquire and process TAT data – Collect laboratory TAT data from relevant information systems and perform data cleaning and transformation to ensure accuracy and consistency for dashboard integration.
- Create an interactive TAT Dashboard – design a dashboard that allows real-time and historical monitoring of laboratory TAT data
- Enable Proactive Interventions – Provide laboratory managers a tool for detecting delays and insights into TAT patterns, together with workload data, allowing for immediate corrective actions such as staff or equipment allocations as necessary.
- Enhance data insight – provide management insight into laboratory operations and the expected waiting times for the different tests offered by the Pathology department.
- Consultation with domain experts - Collaborate with laboratory professionals and stakeholders to evaluate the dashboard's usability and practical effectiveness in the clinical workflow.

1. Background

1.1 Turnaround Time in Laboratory Medicine

The turnaround time (TAT) of a test is a quality indicator for laboratories, as it indicates the average time taken to process a sample from collection to the result reporting. There are multiple types of turnaround times and these are used depending on what the researcher is exploring.

The turnaround time that is most frequently used by laboratorians is aTAT; Analytical turnaround time, which measures the time for processes occurring in the laboratory, from receipt of a test request to the issuing of the result [7]. Clinically, the therapeutic turnaround time (tTAT) also considers the time taken for blood-letting before the sample is sent to the laboratory [7]. These parameters are regularly monitored, as an increase in these indicators can uncover an underlying issue with the testing process [7].

1.1.1 Brain-to-brain loop concept

The laboratory testing process can be divided into a 9 step cycle, that is often referred to as the brain-to-brain loop (Figure 1). The name suggests that the process begins and ends in the physician's brain i.e. where the test order begins, and where it is finally interpreted and acted upon. Should any part of the cycle be broken, it's as if the test was never ordered in the first place;

> *"Unless the appropriate action occurs, it is as if the cycle had never begun and is, at the most, a tragedy and, at the least, a waste."* [8]

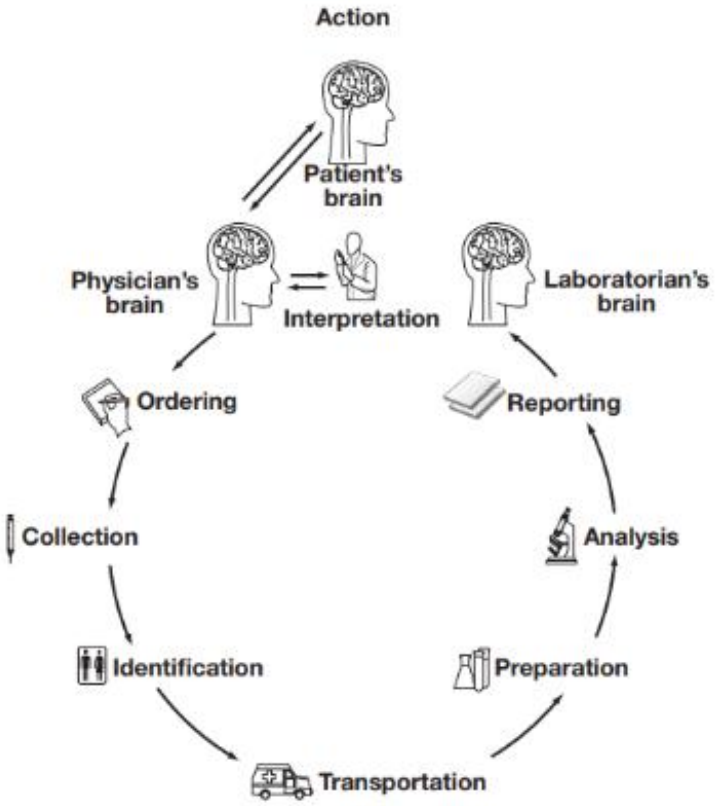


Figure 1: The brain-to-brain TAT loop. Adapted from [9]

This loop encompasses many processes, each having their own risks; selecting the relevant testing process for the correct patient, obtaining the right results, and finally interpreting the results correctly, and providing the appropriate advice [10].

1.1.2 The total testing process

The processes from the brain-to brain loop concept discussed in the previous section make up the Total Testing Process (TTP); which is composed of three distinct phases namely, the pre-analytical phase, the analytical phase and the post-analytical phase [11]. Figure 2 shows how these processes are divided in the local hospital setting [12]. Figure 3 shows an expanded representation of the Total Testing Process as revised in 2023.

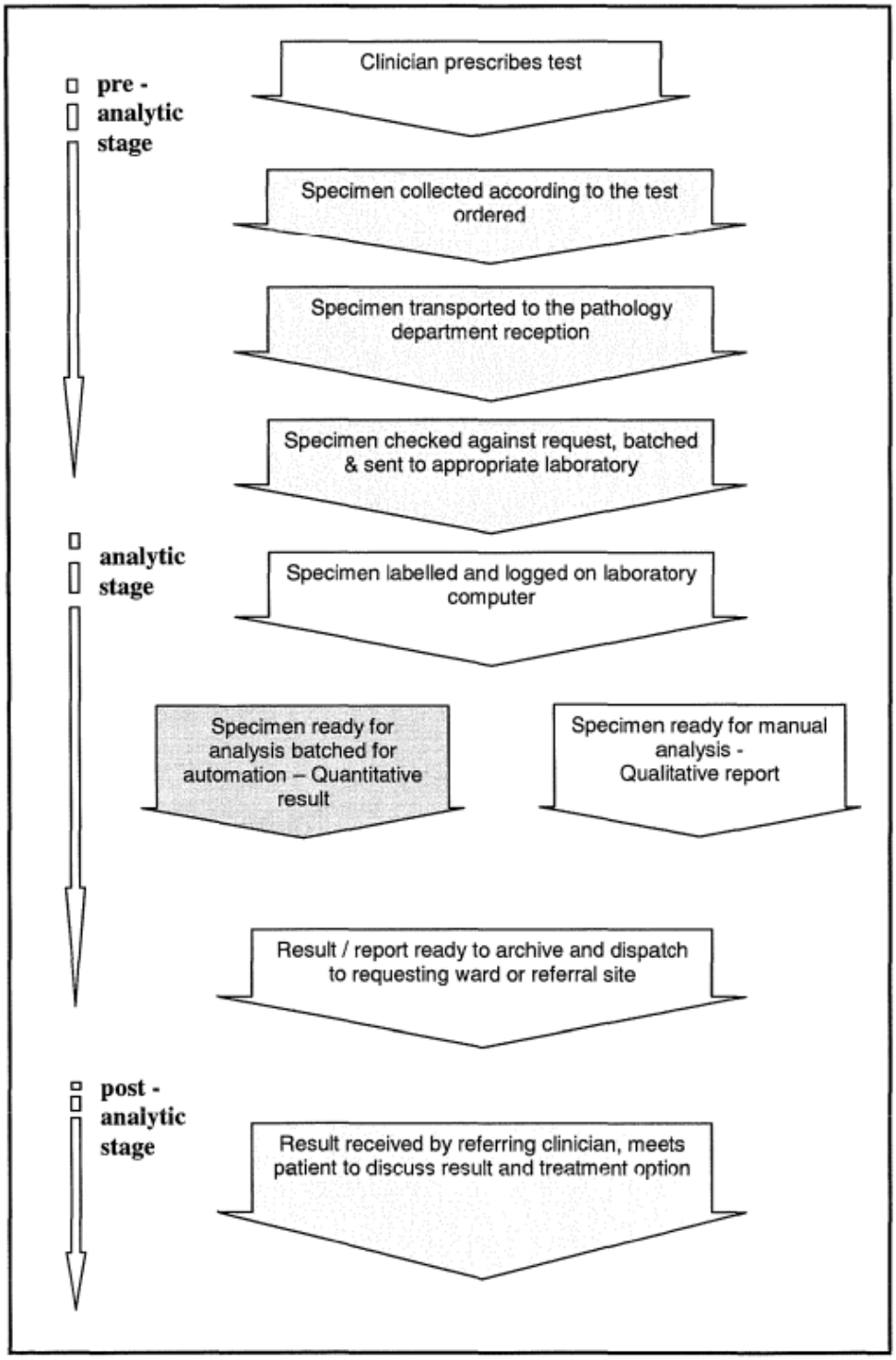


Figure 2 The stages of the total testing process at the Mater Dei Pathology Department. Source [12].

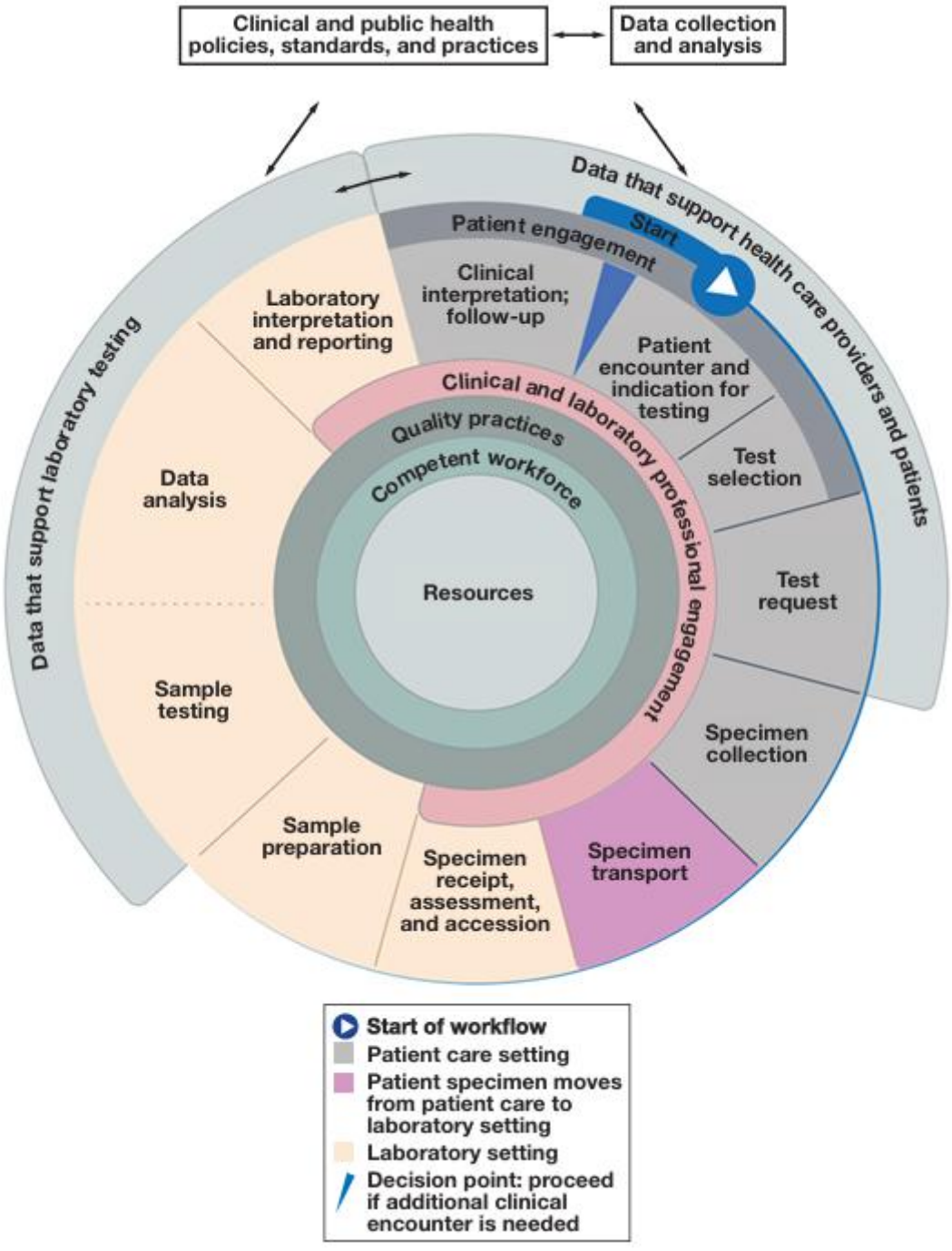


Figure 3 Expanded representation of the Total Testing Process. Adapted from source [13]

1.1.2.1 Pre-analytical phase

The pre-analytical phase includes processes that occur before a sample reaches the laboratory i.e. the interval from when a test is ordered until the specimen is received at the laboratory. These process include the ordering of tests, labelling of specimen, phlebotomy and transportation to the laboratory [14].

1.1.2.2 Analytical phase

The analytical phase includes processes that occur from when the specimen is received to the time that the scientist analyses and releases the result for distribution. These processes include quality control and quality assurance processes, analysis and issuing of results [14].

1.1.2.3 Post-analytical phase

The post-analytical phase is made up of processes occurring from when the result is verified to the time it reaches the clinician who sees it, including the final interpretation of the clinician [14].

The pre-analytical and post-analytical phases of the total testing process are much more prone to errors than the middle analytical phase which is controlled to a greater degree by medical laboratory scientists. These errors can ultimately result in diagnostic errors that can significantly harm the patient [10], such as delays in reporting, where following Lundberg's definition of CAVs [8], the associated harm may be life-threatening if no action is taken quickly. Another post-analytical failure linked to the reporting of CAVs is the failure to reach the responsible practitioner, where the brain-to-brain loop is broken and this is equivalent to the test not being ordered/processed at all [10, 8].

1.2 Laboratory Information Systems

Laboratory Information Systems (LIS) are digital platforms designed to capture, manage, and store patient testing data, with many systems also incorporating decision-support functions to optimise workflow and support point-of-care testing. Modern LIS solutions are widely available, with most

vendors offering adaptability and customisation to meet the specific requirements of individual laboratories [15].

A well-structured LIS generally includes several functional modules. Test ordering functionality allows healthcare providers to submit requests directly into the system, with the capacity to transmit orders seamlessly to connected platforms. Specimen accessioning and processing features include barcode generation and scanning to ensure accurate patient identification and reliable sample tracking. In the analytical phase, LIS integration with analysers ensures that test orders are transmitted automatically to instruments, reducing manual entry and error. Result entry and validation functions enable laboratories to manage reports in different data formats, incorporating both automated and manual result entry, and data exchange with referral laboratories. Advanced systems also support critical result notifications, alerting clinicians when immediate intervention is required. Beyond operational tasks, LIS facilitate data management by enabling analysis of laboratory performance indicators, including turnaround time, to identify areas for improvement. Furthermore, aggregated data can be used for research, epidemiological monitoring, and public health reporting, including the generation of surveillance statistics for notifiable diseases [15].

1.3 Key Performance Indicators

1.3.1 Definition

Key Performance Indicators (KPIs) are measurable variables designed to assess how effectively strategic and operational objectives are achieved. They act as management mechanisms that enable organisations such as laboratories to observe, regulate, and appraise processes in relation to defined performance standards, making it possible to identify and correct deviations from expected outcomes [16]. KPIs establish a systematic approach for benchmarking actual results against set targets, thereby transforming organisational goals and priorities into quantifiable outputs [17]. Their successful application depends on embedding them within a structured quality management system, where

they serve to align institutional strategy with daily operations, inform remedial actions, and drive sustained improvements in quality and efficiency [6, 18].

1.3.2 Metrics vs Key Performance Indicators

The terms metrics and Key Performance Indicators are often used interchangeably but are conceptually distinct. Metrics are general quantitative measures that provide descriptive information about laboratory processes or outputs, such as daily test volumes or the median turnaround time. While these measures are valuable for monitoring activity, they are not necessarily aligned with strategic objectives. By contrast, KPIs represent metrics chosen intentionally because they are explicitly linked to organisational priorities and are therefore critical for evaluating performance. For instance, while the median turnaround time for a test may be considered a useful metric, the percentage of urgent samples reported within a specified timeframe constitutes a KPI, reflecting compliance with service targets. By definition, all KPIs are metrics, but not all metrics are KPIs; the distinction lies in their strategic alignment and their role in supporting benchmarking, decision-making, and accountability in laboratory quality management [16, 17, 6, 18].

1.4 Dashboards

Since hospitals operate in a complex and dynamic environment, offering a wide range of diagnostic, therapeutic, and administrative services, this necessitates continuous performance monitoring across various departments to ensure efficient resource management and high-quality healthcare delivery [19]. Therefore, healthcare providers must access essential information through a structured and systematic method [20].

Dashboards are data management tools that gather information from multiple systems within an organisation and present it through key performance indicators with status alerts. This data is presented on dashboards as colour-coded graphical displays, which are easy to read. Dashboards provide a concise, comprehensive, and meaningful overview, enabling managers to evaluate departmental performance, detect issues, and analyse their root causes. This process helps in making informed decisions to enhance overall efficiency and effectiveness [21, 22].

1.5 National Healthcare Context

Malta's healthcare system is tax-funded and provides universal access to diagnostic services, with acute secondary and tertiary care delivered predominantly through Mater Dei Hospital, the country's main public hospital. Public primary healthcare services are provided through government health centres, with laboratory investigations requested in these settings processed centrally at Mater Dei Hospital, positioning pathology services as a shared diagnostic resource across both hospital and community care settings. Pathology services at Mater Dei Hospital function as a centralised diagnostic hub, supporting emergency, inpatient, and outpatient care [23].

The opening of Mater Dei Hospital in 2007 was accompanied by significant investment in health information systems, including the implementation of an integrated laboratory information system [23]. While these systems routinely capture detailed operational data, such data is often underutilised for real-time performance monitoring. This gap underlines the relevance of dashboard-based approaches to enhance visibility of pathology service performance and support data-driven laboratory management.

2. Literature Overview

This chapter reviews the literature relevant to laboratory turnaround time, healthcare performance dashboards, and the use of data visualisation tools in clinical laboratory and healthcare settings. The literature was identified through a structured search of electronic databases, primarily PubMed, Google Scholar, and IEEE Xplore, to capture peer-reviewed biomedical, laboratory medicine, and health informatics research. Additional sources were retrieved from the University of Malta institutional repository (OAR) to include locally relevant academic work.

Search terms included variations and synonyms of *laboratory turnaround time, laboratory information systems, healthcare dashboards, performance monitoring, and quality indicators*. Inclusion criteria comprised peer-reviewed articles published in English, with a focus on hospital or clinical laboratory environments. Studies addressing performance monitoring, quality improvement, and digital analytics tools relevant to laboratory and clinical operations were prioritised. The literature was assessed for methodological quality and relevance to the research objectives, with an iterative search process that included screening reference lists of key publications.

In addition, technical documentation, best practice guidance, and industry sources relevant to dashboard development and business intelligence tools were consulted from authoritative professional platforms, including Microsoft documentation, World Health Organization publications, and selected vendor literature. This approach ensured a robust and evidence-based foundation for the literature review.

2.1 The significance of Turnaround Time in Laboratory Medicine

Turnaround Time (TAT) is widely recognized as a key performance indicator (KPI) in laboratory medicine because it determines how quickly test results become available to guide clinical management. A shorter TAT ensures that clinicians can diagnose conditions and initiate treatment without unnecessary delay, which is especially critical in acute care and emergency settings. Evidence shows that delays in laboratory reporting can directly extend a patient's stay in the emergency department [1].

The value of actively monitoring TAT was demonstrated in a high-volume laboratory in South Africa, which used a real-time dashboard to track performance and achieved a dramatic increase in the proportion of tests reported within target timeframes—from 10% to over 90%—while halving the 75th percentile TAT from 10 hours to less than 5 hours [6]. Such improvements not only enhance efficiency but also enable faster clinical responses and better allocation of healthcare resources.

2.1.1 Factors Influencing Turnaround Time

TAT in laboratory medicine depends on multiple variables spanning the pre-analytical, analytical, and post-analytical phases. Each stage introduces potential delays that can extend the overall reporting timeline.

Pre-analytical factors include test ordering practices, patient preparation, specimen collection, labelling accuracy, and transport logistics. Inefficiencies such as delays in phlebotomy, batching of samples, or long courier times frequently account for the largest share of TAT variability [24, 1]. A systematic review of 7 articles, by Negesse et al (2024) confirmed that pre-analytical steps—particularly specimen transport and registration—are major contributors to extended TAT in hospital laboratories [25].

Delays in the analytical phase may arise from equipment downtime, sample reruns, or inefficient analyser-to-LIS interfacing. The application of Lean and

Six Sigma methodologies has been shown to reduce such inefficiencies, with studies reporting TAT reductions of up to 76% following process redesign [25].

Post-analytical delays may occur if results require manual checking, if critical results must be phoned to the ward, or if there are bottlenecks in LIS interfaces with other systems. In some settings, post-analytical delays are among the most frequent sources of prolonged TAT, as results can remain pending until formally validated by laboratory staff. Hawkins highlighted that the reporting stage often contributes to clinician dissatisfaction when delays arise, even if the analytical process was completed promptly [24]. Studies have also shown that automation of post-analytical workflows—such as auto-verification protocols and direct electronic release of normal results—can significantly shorten reporting times while allowing staff to focus on result exceptions [26].

Beyond specific workflow inefficiencies, other broader systemic pressures may have a significant impact on TAT. Staffing shortages, particularly evident during the COVID-19 pandemic, placed heavy strain on laboratories, increasing workloads and slowing result reporting [27]. Also, interoperability of LIS strongly affects efficiency: modern LIS platforms that integrate seamlessly with electronic health records and analysers can reduce delays, while siloed systems often create bottlenecks [28].

2.1.2 Effect of Delayed TAT

Medical laboratories are expected to provide reliable and accurate results within an appropriate timeframe to ensure high-quality diagnostic services. Result accuracy is ensured through validated analytical methods, regular equipment calibration, strict adherence to standard operating procedures, and participation in internal and external quality assurance programs [29]. Proper patient identification, sample collection, and specimen transport further help maintain result integrity. However, result quality also depends on timeliness. Turnaround Time (TAT) is a critical indicator of laboratory efficiency, as delays can hinder diagnosis, treatment, and patient care. Achieving a balance between analytical quality and prompt reporting is therefore essential for maintaining overall laboratory performance. Shorter turnaround times enable clinicians to deliver care more promptly, whereas reporting delays can

postpone both diagnosis and treatment. Evidence shows that prolonged TATs may extend patients' length of stay in emergency departments [2]. An increase in the length of TAT can also have an impact on the number of requests received by the laboratory due to duplication of requests, impacting the effort of the laboratory and contributing to higher health care costs [30].

2.1.3 TAT improvement measures

Improving turnaround time (TAT) in the clinical laboratory requires coordinated interventions across all workflow stages. At the pre-analytical level, this includes standardising test ordering through the LIS, accurate patient identification, and proper specimen labelling, supported by trained staff and reliable transport systems that ensure traceability and accountability. During accessioning, technologies such as pneumatic tube systems, barcoding, and personnel training can minimise delays. Within the analytical phase, automation of testing, consistent quality control practices, regular instrument maintenance and automated result verification help to streamline processes. For the post-analytical stage, integrating analyser outputs with the LIS, direct electronic release of results, and minimising manual data entry reduce reporting errors and delays. More broadly, continuous monitoring of TAT metrics, daily review of performance, and prompt corrective action to address errors or inefficiencies support sustainable improvements across the testing cycle [31].

2.2 Tools and Techniques for TAT Monitoring

This section describes how data for TAT can be gathered and what tools and systems have been described for the monitoring of TATs.

2.2.1 Data Gathering from Laboratory Information System

The Laboratory Information System records timestamps at each stage of the laboratory testing process. These timestamps are triggered by system-triggered events or manual data entry. These stamps usually include: test order entry,

sample collection, sample receipt, result validation and result release time. Some systems may also include the start and completion time of analysis.

These timestamps can be extracted from the LIS database via built-in report functions, SQL queries or middleware systems, to compute TAT trends.

2.2.2 Technological Tools and Systems

2.2.2.1 Spreadsheets

The use of spreadsheet software such as Microsoft Excel, remains a popular option for TAT data manipulation, especially when there are financial constraints for adopting other software. A benchmarking survey in 2021 showed that 80% of hospital laboratories and 50% of commercial laboratories rely on Microsoft Excel for the analysis of TAT data from LIS timestamps [32].

Some entities also use spreadsheets to perform initial calculations on raw data, before migrating the data to Business Intelligence (BI) tools for more interaction [6].

2.2.2.2 LIS

The Laboratory Information System (LIS) plays an essential role in monitoring turnaround time (TAT) by capturing time stamps at critical points in the testing workflow, such as sample collection, analysis, authorisation, and release of results. These data elements make it possible to retrospectively analyse TAT performance and to produce reports that reflect compliance at the level of individual assays, laboratory sections, or the wider organisation [24]. In most laboratories, LIS-derived monitoring remains retrospective, relying on periodic data extractions rather than continuous oversight, which reduces its utility for identifying delays in real time [6].

2.2.2.3 Middleware

Although the LIS forms the backbone of laboratory workflow and information management, middleware has emerged as the most effective tool for monitoring TAT in real time. Middleware functions in the intermediate layer between analysers and the LIS, automatically recording instrument time stamps and applying rule-based processing before results are transmitted. This capability allows laboratories to track the progress of specimens through the

analytical pathway, and receive immediate alerts when delays occur [24, 6]. By contrast LIS reporting is frequently retrospective. Middleware therefore, provides laboratories with a distinctive advantage by enabling proactive oversight of TAT, offering continuous operational feedback that LIS is not designed to deliver [24, 6]. Middleware, however is usually analyser or manufacturer-specific, and different middleware may be in operation concurrently in the same laboratory due to multiple analyser manufacturers. Therefore, middleware may not be the ideal solution to give an overview of the laboratory's performance across all the testing portfolio (see Section 2.5.1 Middleware Solutions).

2.2.2.3 Business Intelligence and Dashboard Tools

The application of business intelligence (BI) software and dashboard technologies has become an important approach for improving turnaround time (TAT) monitoring in clinical laboratories. These systems extract and process data from the laboratory information system (LIS) to create interactive visual displays and performance metrics that extend far beyond static reports. Unlike traditional retrospective reporting, BI dashboards enable near real-time visualisation of TAT compliance, presenting information in formats such as trend lines, charts, and colour-coded alerts that make deviations from benchmarks readily apparent [33, 6]. By incorporating indicators such as median TAT, percentile distributions, and delays in specific workflow phases, dashboards translate raw LIS data into actionable intelligence. In doing so, they support timely managerial decision-making, facilitate early intervention in bottlenecks, and contribute to a culture of continuous quality improvement in laboratory services [34, 6].

2.2.2.4 Machine Learning Models

Machine Learning (ML) Models have been proven to accurately predict TAT in laboratories, whilst identifying the most influential factors contributing to prolonged TATs. ML can aid the lab in taking timely action, addressing cases of predicted prolonged TATs and improving planning of scarce resources [35, 36].

2.3 Metrics and Key Performance Indicators in TAT Monitoring

2.3.1 Common KPIs for TAT Assessment

2.3.1.1 Mean and Median TAT

Different measures can be used to describe TAT, and their different use across laboratories can make comparisons complicated. The overall processes covered by TAT is made up of several sequential steps, some of which may have a fastest time possible e.g. if a certain test is carried out on serum, the blood sample received at the laboratory has to be centrifuged to separate the serum from the red blood cells; this process is a standardised procedure which takes 10 minutes and cannot be shortened, but can only be delayed in the case of centrifuge malfunction. Due to the nature of these processes, Gaussian distribution cannot be achieved for each of the steps in the process, and thus Gaussian distribution cannot be expected for the total TAT. Hence the use of standard deviation and means alone in the case of TAT is inappropriate [24]. Non-parametric statistics, such as median, frequency distributions, and percentiles, are more appropriate for TAT monitoring [37]. However, the mean has been identified as a metric with a high reproducibility and this property holds value in cases of tests with long TATs [24]. In cases of more rapid TATs, the outlier rate described below is more suitable, as this metric is more sensitive and specific for detecting a drop in TAT below the set standard [24].

2.3.1.2 Percentage Within Target TAT and Outlier Rate

TAT can also be reported by the number of reports delivered within a consensually agreed time, which is expressed as a percentage of the total number of reports. Conversely, one can also report the percentage of the number of reports delivered outside the specified time over the total number of reports [38]. This is defined as the outlier rate corresponding to the tail size of the non-Gaussian distribution. This tail size can also be represented as a time value corresponding to a specific percentile of the distribution (e.g., the 90th

percentile). This is also commonly expressed in literature as the 90% completion time [24].

The combination of measures such as the median as well as the tail size (outliers) measures allows a more comprehensive analysis of TAT without focusing too much on a single parameter [39].

2.3.2.3 Cumulative TAT Distribution

Another approach in literature to analyse TAT is the use of failure time analysis including Kaplan-Meier survival curve plotting, Cox proportional hazard model and log-rank tests [40]. The Kaplan-Meier survival curve is usually used for calculations of survival rates. In the case of TAT, the active samples are treated as living patients, where the sample completion time is equivalent to the time of death of a patient, and the survival time is equivalent to the time lapse from registration to completion. This approach allows the application of survival rate calculation methods to TAT. This method allows visualisation of TAT performance whilst also enabling the comparison of different distributions e.g. routine vs urgent samples, by using the log-rank test. The Kaplan-Meier curve can also handle incomplete data, such as for samples that are still pending and have not gone through the whole process up to result validation [41, 40].

2.3.2.4 STAT vs Routine TAT Compliance

Tests carried out in a medical laboratory can be requested either as a routine test or an urgent test, also referred to as STAT, depending on the patient case and the nature of the test. TAT plays a very important role in tests ordered as urgent priority, as delays in these cases can significantly impact patient care. The evaluation of TAT must take into consideration the order priority of the samples and thus two TAT targets are usually set, with the urgent priority tests having a much shorter target TAT, usually less than an hour, than the routine priority tests. Urgent/STAT test TATs are considered the most important measure of laboratories functioning [42]. The expression of the difference between median routine TAT and urgent TAT as a percentage of the median urgent TAT, can indicate operational efficiency and the responsiveness of the

lab to urgent testing, whilst helping in identifying bottlenecks in lab processes [43, 44].

2.3.2.5 Results Notification TAT

Results notification TAT is the time from result availability in the LIS to communication with the clinician, capturing the post-analytical dimension of laboratory performance. Although less frequently monitored than analytical TAT, it is highly relevant for urgent or critical results, where delays in notification can directly affect patient care [24, 38]. Incorporating this metric as a KPI extends TAT monitoring beyond laboratory processing to include the effectiveness of result reporting and clinician communication, thereby providing a more complete picture of laboratory responsiveness and its impact on clinical decision-making [45].

2.3.2 Establishing KPI Benchmarks and Standards

For Key Performance Indicators (KPIs) to be meaningful, laboratories must establish clear benchmarks and reference standards to compare their KPIs to. Benchmarks provide the yardstick for judging performance, enabling laboratories to assess whether results meet internal expectations or compare favourably with external peers. Within laboratory medicine, these benchmarks are frequently informed by international regulations and accreditation frameworks, such as ISO 15189:2022, which requires the systematic use of quality indicators to evaluate services that affect patient care [29]. Professional organisations and external quality bodies also propose recommended limits for turnaround time, error rates, and critical result communication, which laboratories can adopt or adapt depending on their context [45, 46, 38].

There are several approaches to setting standards for KPIs. Some laboratories adopt evidence-based targets, where thresholds are informed by studies linking performance to clinical outcomes [24]. Others implement consensus-based values, developed through national schemes, regional networks, or professional groups that encourage harmonisation across institutions [46]. In practice, most laboratories combine internal benchmarking, based on their own historical data, with external comparisons to ensure that targets are both achievable and clinically relevant. For instance, a KPI specifying that “90% of

urgent tests should be reported within 60 minutes" provides a measurable and clinically meaningful threshold. KPI standards should be reviewed periodically to ensure they remain aligned with technological advances, evolving clinical priorities, and updated regulatory requirements.

2.4 Dashboard Technology in Healthcare

2.4.1 Applications of dashboards in healthcare

Two main types of dashboards are used in healthcare: clinical and quality. With clinical dashboards, the aim is to provide relevant information to the healthcare professional, aiding decision-making about patients, e.g. a dashboard to aid the physician in antibiotic prescribing [47]. The local hospital, Mater Dei Hospital, makes use of a clinical dashboard, aptly named 'Patient Dashboard', to gather information from different information systems used in the hospital, allowing clinicians to have an overview of investigations, case summaries, past and pending appointments, procedures, alerts and documentation for the same patient without having to reference multiple applications [48]. On the other hand, quality dashboards provide insights to managerial staff about key performance indicators (KPIs) and processes, helping with decision-making [49, 50].

Performance dashboards can also be classified as strategic dashboards, tactical dashboards and operational dashboards [51]. Strategic dashboards are designed for management purposes to evaluate strategic objectives execution, rather than to analyse and monitor metrics. One example of such a dashboard is described by Pace and Buttigieg, where an objective was set for 95% of patients at the accident and emergency department to be discharged within 4 hours [52]. Tactical dashboards are used to track processes and focus more on analysis. Tactical dashboards can also be used to monitor performance against other goals and budgets and are usually used to monitor data daily updating data periodically. In Pace and Buttigieg's study a tactical dashboard was used to generate daily information about whether the target set at a strategic level was met. This allowed the analysis of factors that were causing delays in waiting times in the department. Finally, operational dashboards allow users

to monitor core processes in real time. Operational dashboards allow the visualisation of timely information, aiding their decision-making process e.g. a screen at the accident and emergency department viewable by clinicians showing the status of patients currently in the department and their status [52, 21].

These different types of dashboards are ideally used together to obtain the greatest benefit, where there is synchronisation between the planning and implementation, having a cascading effect from the strategic to the tactical and operational levels [53].

2.4.2 Challenges in healthcare dashboards

The design and implementation of effective healthcare dashboards face several challenges spanning technical, organisation and human factors, which can all significantly affect the adoption and utility of dashboards in clinical settings. This section describes some of these challenges that are highlighted in the literature.

2.4.2.1 Data sources and data generation

A healthcare dashboard may require the integration of different data sources, often stored in siloed systems such as the laboratory information system (LIS), electronic health records (EHRs) and radiology information systems (RIS). These may use different standards and data formats, lacking interoperability, making data integration difficult.

2.4.2.2 Dashboard Content

Selecting meaningful content for healthcare dashboards is a persistent challenge. Dashboards must balance simplicity with comprehensiveness, ensuring that key indicators are clinically relevant without overwhelming users with excessive data. Poorly chosen metrics risk limiting usefulness, while the absence of standardised indicators across institutions can reduce comparability and benchmarking value [54].

2.4.2.3 Dashboard Design

Effective dashboard design depends on presenting complex data in a way that is clear, accurate, and easy to interpret. Poor layout, excessive information, or

inappropriate visual choices can confuse and hinder decision-making. Research shows that user-centred design, where users are actively involved in development, is critical to ensure dashboards fit naturally into workflows [54]. Beyond visual considerations, dashboards must also address both functional requirements—such as appropriate indicator selection and interoperability—and non-functional requirements, including usability, system performance, and security, which strongly influence user acceptance [55].

2.4.2.4 Implementation and Integration

Even when well designed, dashboards often encounter challenges during implementation. Integrating dashboards into existing health information systems can be complex, particularly when dealing with interoperability gaps or varied local IT infrastructures [56]. Organisational readiness also plays a significant role; factors such as leadership support, staff training, and user engagement determine whether dashboards are successfully embedded into routine practice [54]. In addition, ignoring non-functional requirements—such as adequate training, data governance, and system sustainability—can undermine adoption and long-term utility [57].

2.4.3 Key considerations in dashboard design

This section describes the guidelines and principles to be considered when developing dashboards, emerging from literature and guidelines such as the Nielsen Usability Heuristics [58] and Microsoft Power BI dashboard design guidelines [59]. These principles help create healthcare dashboards that present data whilst empowering users to make timely, informed decisions, improving operational efficiency.

2.4.3.1 User-Centred Design and Usability

The first crucial step when designing a dashboard is to identify the target audience and their specific goals and needs [60]. Different stakeholders, such as clinicians, administrators, executives or researchers, would have different informational needs for the same setting e.g. executives may need high-level overview data, whilst clinicians would require more granular patient-level details for immediate care decisions. Dashboards should be designed with the

user in mind, their technical expertise, workflow, as well as the organisation's objectives to increase usability and relevance [61, 59].

2.4.3.2 Simplicity and Focus

A core principle outlined in various dashboard guidelines for effective dashboards is the importance of a clean and simple layout without overwhelming and excessive information and visual elements on a single screen [62, 63]. Each extra bit of information competes with other information that may be more relevant, and may diminish its visibility [58]. Ideally, dashboards fit within one screen, avoiding scroll bars, enhancing usability [62].

2.4.3.3 Choosing the Right Visualisations

Although tools such as Power BI offer a variety of visualisations, these must be chosen carefully according to the target audience and the type of data being visualised. Pie and doughnut charts must be avoided, as these are difficult to interpret accurately by the human brain [63, 59, 64]. Bar and column charts are preferred when the scope of the visual is to compare data, whilst line charts are effective to visualise trends over time. Other visuals would be appropriate according to the data type, e.g. maps when displaying geographical data, and gauge charts when displaying a status in relation to a set goal [60, 59].

2.4.3.4 Choosing the Right Colours and Formatting

Colour and formatting in dashboards must be used carefully, emphasising clarity and readability, whilst maintaining consistency in colour choices. Colour must be used sparingly and only when information needs to be highlighted, using colours that adhere to colour accessibility guidelines, making the dashboard accessible to users with colour-blindness [60, 62]. Numerical data must be presented in the appropriate format with scaled numbers that are easier to read, e.g. using 4.2 million instead of 4,200,000. White spacing should also be considered, with sufficient space between different elements to improve comprehension and decrease clutter [63, 59].

2.4.3.5 Hierarchy, Layout and Consistency

The visualisations used must be arranged in a way that provides a narrative flow with high-level overviews at the top, with more detailed information as

one goes to the bottom of the dashboard. One should also maintain consistency and standards across the dashboard to improve usability and learnability for the users as well as reduce cognitive load [60, 63, 59, 58].

2.4.3.6 Interactive Elements

The usability of a dashboard can be enhanced by including interactive features such as slicers, filters and drill-through functionalities. These features enable the user to explore the data according to their needs [65, 60]. However, one must keep in mind that each level of interactivity slows down the loading times of the report, and so a balance must be achieved between the speed of the loading time and the interactive elements added to the dashboard [60].

2.4.3.7 Data Accuracy, Reliability and Transparency

The use of data that is accurate, up-to-date and reliable is crucial to achieve accurate insights into the data, on which informed decisions can be taken. To maintain high-quality data, data transformation and cleaning procedures are applied, whilst ensuring transparency by providing clear data sources to build the user's trust [62, 65].

2.4.3.8 Data Security and Privacy

Depending on the type of data used for the dashboard, data security and privacy measures must be implemented, such as encryption, user access controls and role-based security. This is especially paramount when sensitive healthcare data is used for the dashboard. Patient privacy must be protected by the de-identification and anonymisation of data whenever possible [65, 61].

2.4.3.9 Responsiveness and Accessibility

For a dashboard to be effective, it must be usable and responsive across different screen sizes and devices, allowing different users to access the dashboard irrespective of the device being used [59]. Backend structure, which can include middleware and data warehouses, must be robust to allow the dashboard to have a sound architecture, providing real-time data without lag [57].

Accessibility for users with different needs must also be considered, where keyboard navigation or screen reading may be needed. The use of colour,

symbols and text should also take into account how these may be perceived by different cultures, where they can even be seen as offensive [65, 66].

2.4.3.10 Selecting Relevant Key Performance Indicators

Key Performance Indicators (KPIs) are essential in dashboards to provide actionable insights. These KPIs should be relevant to the target audience of the dashboard, as well as the organisation's objectives. The number of KPIs used should be limited to maintain focus without overwhelming the user. KPI visuals require a measure which is measured against a target value, where the progress towards the target value is communicated [62, 67].

2.4.3.11 Regular Evaluation and Iteration

Designing a dashboard should not be treated as a one-off task, but as an iterative process where users are consulted for feedback, continuous evaluation is carried out, and engagement is monitored. Information from different stakeholders can be used to identify areas for improvement and ensure that the dashboard remains relevant [68]. The KPIs used in a dashboard may also need revising periodically as their relevance may change over time and may need revising periodically [69]. The engagement of health professionals across the development stages, from initial consultation to implementation follow-up, will keep the dashboard relevant to their needs [70].

2.5 Case Studies and Existing Solutions

2.5.1 Middleware Solutions

In clinical laboratories, middleware functions as an intermediary between analysers and the laboratory information system (LIS). These platforms facilitate workflow management by handling result routing, auto-verification, workload distribution, and instrument connectivity. For TAT monitoring, middleware offers clear advantages: it records detailed timestamps during analytical processing, generates real-time dashboards, and highlights performance trends that enable laboratories to address bottlenecks and

improve throughput. Within the analytical phase, middleware can therefore be an effective tool for enhancing efficiency and supporting timely reporting.

However, these strengths are counterbalanced by significant limitations. Many TAT-monitoring capabilities are embedded in proprietary middleware, such as vendor-specific systems or workflow platforms. Because such systems focus only on the processes they directly control, they tend to capture a restricted segment of the testing pathway. Analyser middleware, for example, can accurately report analytical processing times but provides limited visibility into pre-analytical activities or post-analytical steps. This restricted perspective produces partial TAT metrics that do not represent the full testing cycle. Furthermore, proprietary middleware frequently operates in isolation from LIS, creating data silos that fragment operational insights and limit organisation-wide analytics.

A prime example is Roche's *navify Lab Operations* and *navify Analytics for Core Lab* [71, 72]. These platforms reliably monitor analyser functions, process delays, and production metrics. They also offer some monitoring of pre-, analytic, and post-analytic intervals, yet they still rely on structured inputs from different systems. Because each middleware platform typically produces its own dataset, insights remain scattered: one system may highlight analyser throughput while another points to validation delays, but no unified framework connects all phases of the TAT lifecycle. In this case, these platforms would only monitor their own manufacturer's systems, and do not give any insight into other laboratory tests that are performed outside of this scope. Overcoming these siloed data structures often requires costly customisation or extensive integration projects, limiting scalability and interoperability.

2.5.2 Dashboard for COVID-19 Diagnostics Management

Facing the COVID-19 pandemic in 2020, there was a surge in requests for Polymerase Chain Reaction (PCR) testing of SARS-CoV-2 RNA in patients with suspected COVID-19. The Institute of Microbiology (IMU), located in Switzerland, developed a dashboard to monitor Key Performance Indicators during these periods of intensive testing, representing data in a more user-

friendly approach. Previously, data to monitor KPIs was assimilated manually from various sources using repeated manual actions, making the process prone to error and especially challenging when faced with the diversity and vast amount of data being generated. [73]

The developed dashboard monitored the demographics of the patients together with the positivity rate. The number of samples being received hourly, as well as the number of results being issued hourly, were visualised (Figure 4) as well as the average test duration over time (Figure 5). This enabled the laboratory to continually assess the situation, using daily statistics to adjust human resources and anticipate material resource needs to keep up with the testing demand. The hourly statistics, together with turnaround times, outlined operational issues, e.g. the high number of samples received later on in the day. This type of data allowed the investigation of potential causes of delay, and processes could be fine-tuned for better operations, ultimately benefiting the patient and service users [73].

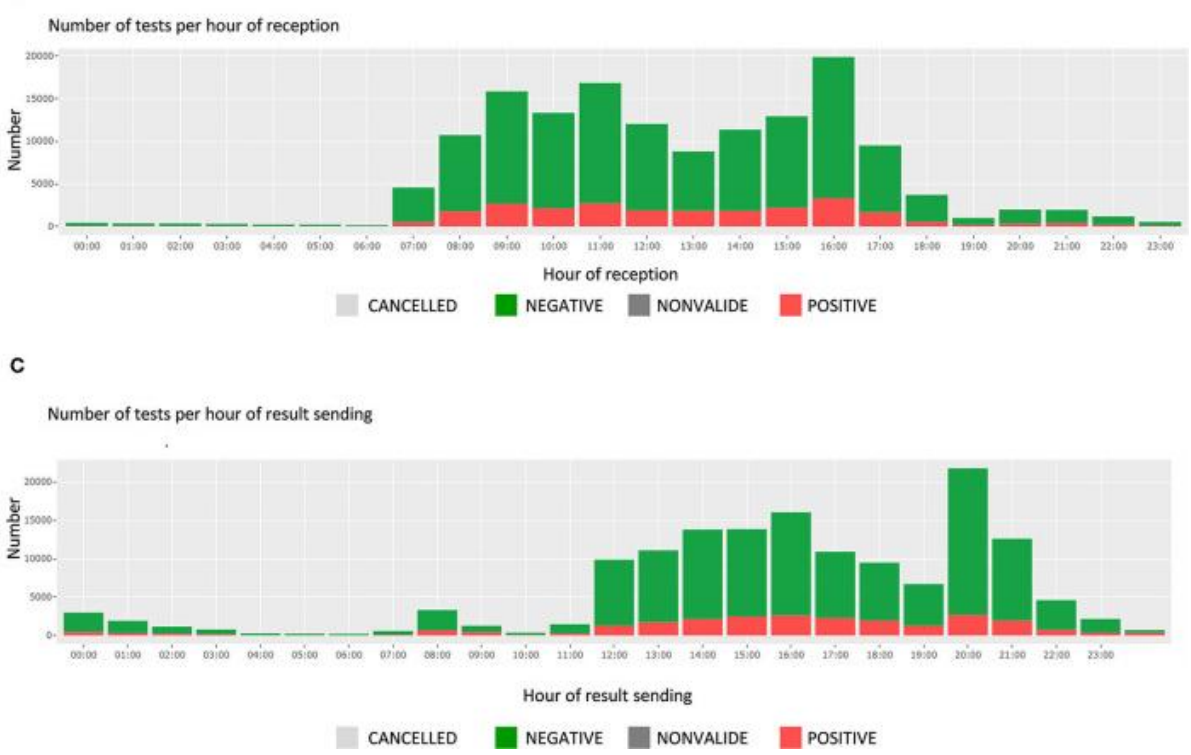


Figure 4 – Dashboard for COVID-19 Diagnostics Management showing number of test requests being requested hourly, as well as number of results being issued hourly. Adapted from Source [73]

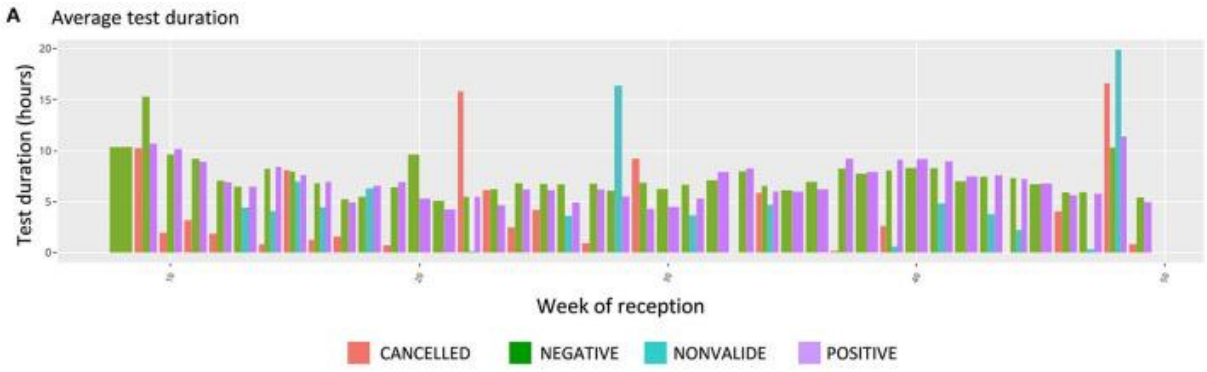


Figure 5 – Dashboard for COVID-19 Diagnostics Management showing average test duration over time. Adapted from Source [73]

An open source tool was developed using R Programming in a study by Rivero in 2020 to enhance data analytics for small laboratories, especially during economic uncertainties such as the COVID-19 pandemic. This tool was developed to give insights into data for individual tests together with economic insight. By analysing data from the different testing phases, one can analyse different KPIs such as the volume of test orders, the test efficiency rate, cost per approved test, operating cost, as well as costs for reagents being utilised [74] (Figure 6).

2.5.3 Radiology Dashboards

The use of dashboards to monitor turnaround times (TATs) has proven highly effective in settings well beyond the laboratory, such as in radiology. A study by Morgan et al found that implementing a digital dashboard containing a real-time, unsigned-report indicator linked directly to report-signing tools reduced the average radiologist report signing time by 24% (from 22.5 hours to 17.7 hours) [75].

In another study at the University of Pennsylvania, a web-based dashboard was developed that provides real-time visibility into the status of pending imaging exams. Deployed across four emergency departments between 2020 and 2021, the dashboard led to sustained engagement and helped clinicians answer patient inquiries about imaging wait times without interrupting

radiology staff, thereby streamlining communication and improving clarity in exam status tracking [76].

These studies underscore a consistent theme: when well-designed dashboards surface the right indicators at the right time, they become powerful tools for performance enhancement and workflow efficiency across clinical disciplines.

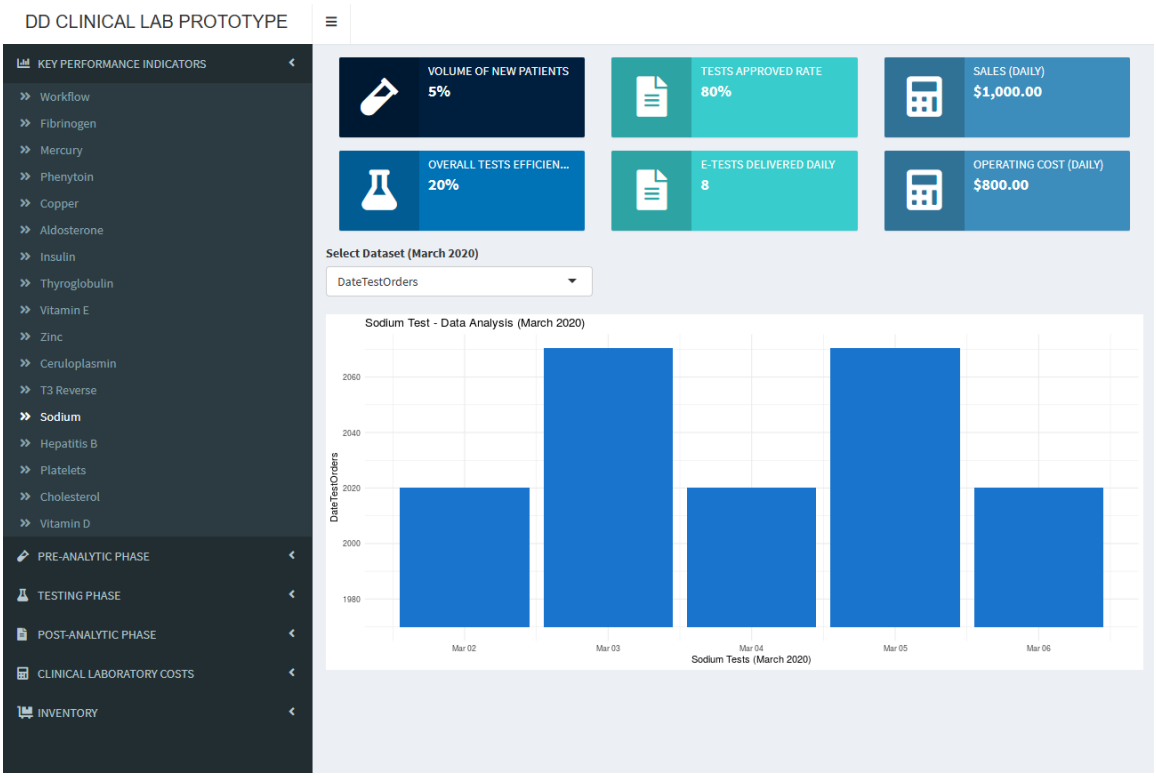
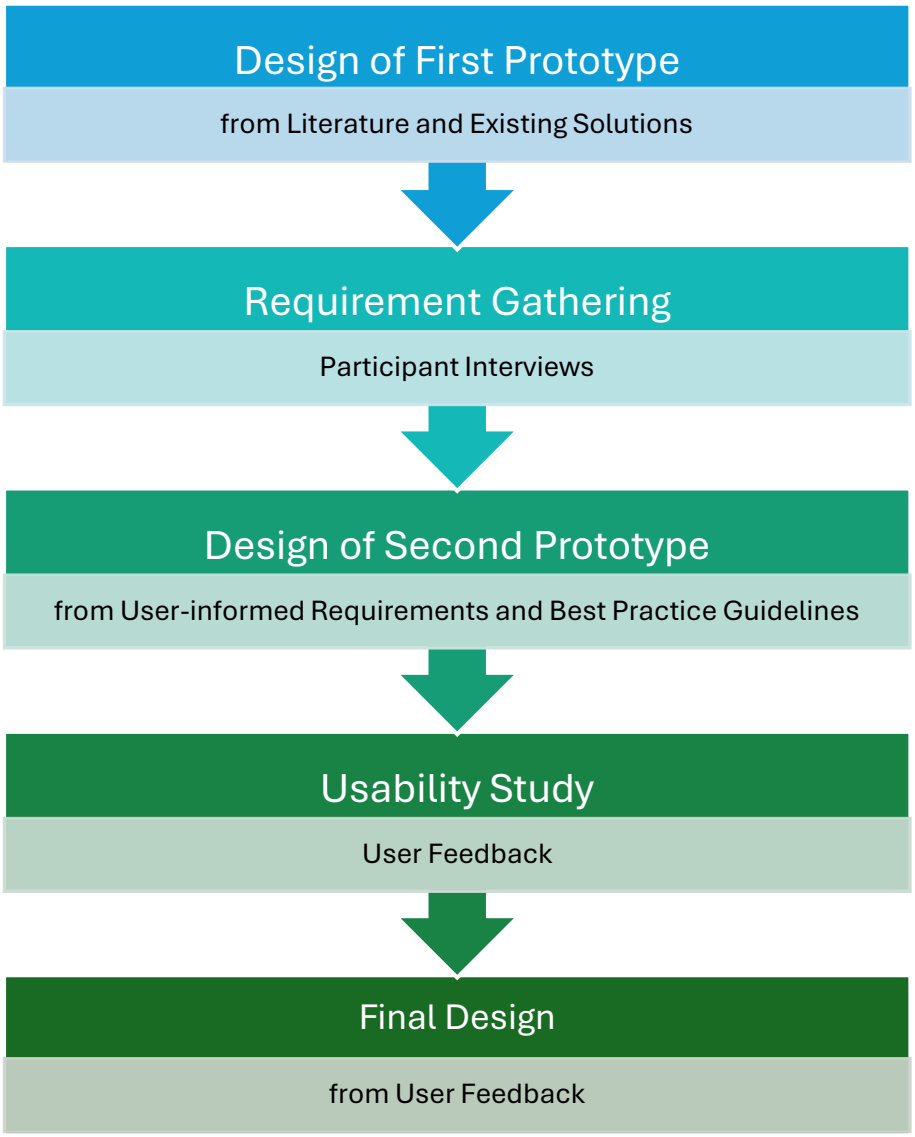


Figure 6 – Screenshot of the DD Clinical Lab Prototype Application; https://mhrivero.shinyapps.io/Performance/ [74]

3 Specification and Design

This section describes the methodology that was used to establish the functional and non-functional requirements for the solution and how user needs were translated into structured specifications for the development process. The design process aims to ensure usability, relevance, and alignment with operational goals, focusing on effective visualisation of relevant metrics for timely decision-making. Below is the development and implementation process described in this and the following chapters.



3.1 Research Ethics

Before commencing the study and data collection, the University of Malta URECA self-assessment form was submitted to FREC. No ethics and data protection issues were identified; thus, the form was submitted for records and audit purposes without FREC review. The information sheet and consent form used for this study were also submitted, a copy of which may be found in Appendix A and Appendix B: Participant Consent Form.

Permission was obtained from Mater Dei Hospital (MDH) to use Pathology Department data and conduct staff interviews for this research.

3.2 Requirements Gathering

Requirements gathering is a critical phase in software development, ensuring the final product meets user and operational needs. It involves systematically identifying and documenting stakeholders' functional and non-functional requirements to ensure the software meets its purpose. In healthcare, this stage aligns system design with clinical workflows and user expectations, enhancing usability and adoption.

3.2.1 Participant Interviews

The target users for the dashboard solution are medical laboratory scientists in management positions who monitor TAT data and would be able to act on such data. Through an intermediary from higher management at the Pathology department, lab managers from different disciplines of the Pathology department that fall within this scope were approached and recruited for an interview. An interview guide was developed to understand the user's background, functional and informational requirements and expectations to develop a user-centred dashboard solution (Appendix C: Interview Guide). A dashboard prototype was also developed in Figma [77] based on the literature and existing solutions. This prototype was used to visualise the concept in the interviews and ask for participant feedback (Figure 7).

Eight participants were interviewed in total, all of whom have a managerial position and use TATs as part of their duties. One of the participants also held an administrative role managing the Laboratory Information System.

Figure 7 First Dashboard Prototype designed with Figma

3.2.2 Interview Key Findings

3.2.2.1 Current TAT Monitoring Practices

The interviews revealed considerable variability in how TAT is monitored across the different sections of the department. Each section employs its own approach to extract, manipulate, and interpret data, often in isolation from a standardised departmental framework.

In sections where TATs naturally span several days to weeks—such as in specialised or complex testing—TAT monitoring is not integrated into daily workflow. Instead, these sections review TATs only when required for departmental statistical reporting.

Across all laboratories, TAT tracking is limited to specific tests representative of the lab performance, and particularly those flagged as urgent, where turnaround time is clinically more significant. Routine test requests are generally not monitored.

TAT data is almost always monitored retrospectively, with only two interviewees reporting access to real-time data owing to their roles as LIS administrators. All other participants rely on retrospective data generated using periodic queries on the LIS database.

Participants consistently reported that their monitoring practices rely on median-based measures, calculated using the analytical phase and post-analytical phase, and excluding the pre-analytical component. They were familiar with reporting TATs using the median, as well as categorical classifications such as within target, within 2× target, and outliers. In contrast, there was little awareness or use of more nuanced indicators, such as Routine vs. Urgent compliance, which remain largely unfamiliar to laboratory users.

3.2.2.2 Main Challenges Identified

3.2.2.2.1 Lack of real-time visibility

A consistent concern across interviews was the inability to monitor TATs in real time. Most reports are generated retrospectively, and thus, managerial staff are unable to intervene proactively in the case of abnormal delays. In turn,

corrective actions are delayed with issues being identified too late to prevent the ultimate impact on patient care or workflow efficiency.

3.2.2.2.2 Fragmented Access and Tool Limitations

Access to TAT data is often restricted to specific individuals—typically LIS administrators—due to software licensing constraints. This limits broader staff engagement in quality monitoring and reduces opportunities for team-wide responsiveness.

Participants expressed interest in using platforms like Power BI or similar tools for dynamic TAT tracking. However, integration between the LIS and these tools is limited, both technically and due to licensing costs. This restricts the ability to develop shared, real-time dashboards tailored to different lab sections or roles. Without such integration, TAT data remains underutilised for process improvement, staffing optimisation, and quality assurance.

3.2.2.2.3 Manual Method of Data Manipulation and Report Generation

All sections currently rely on manual data handling to generate reports, primarily using basic tools like Microsoft Excel and Word. In one section, the process involves working across multiple spreadsheets, visually inspecting data to filter relevant entries, segmenting data by time frames, and calculating various parameters for each period—all performed manually by a single individual. This makes the process time-consuming and inefficient.

In another section, TAT data is automatically extracted weekly from the LIS database through a predefined query, and data processing is semiautomated using templates. However, even in this case, the final report still requires manual data entry, introducing the risk of human error and user-to-user variability, which can compromise the accuracy and consistency of the final data.

3.2.2.3 Expectations for the Dashboard

3.2.2.3.1 Dashboard Features

All interviewees emphasised the need for a simplified method to extract and automatically process data with filtering capabilities. The requested filters included:

- Date
- Test
- Priority (Urgent/Routine)
- Requesting department

There was unanimous interest in a live dashboard featuring real-time alerts highlighting overdue samples. This functionality was essential for identifying delays and addressing issues promptly during active workflows.

The importance of a low-maintenance design capable of handling automatic data refreshes was highlighted, avoiding manual updates to keep the dashboard relevant.

Participants collectively identified several key metrics they would like the dashboard to display:

- Median TAT
- Percentage of tests within and outside target thresholds
- Phase-specific TATs (pre-analytical, analytical, post-analytical)
- Hourly workload metrics
- TAT trends across time (day vs night comparisons)

One user highlighted that TAT statistics should be calculated per test rather than per sample, as additional tests are sometimes added after the initial order. Calculating TAT based on the original sample time in such cases may create a misleading impression of delay.

For visualisation, users favoured line and bar charts to represent trends and distributions, with several suggesting a traffic light system for quick, visual identification of problem areas.

3.2.2.3.2 Dashboard Accessibility

Most participants favoured a desktop-based application, consistent with their workflow. Only 2 participants (25%) expressed interest in having a mobile-accessible version, and even then, this would be alongside the desktop version. This preference reflects both the current workflow with the use of desktop workstations to access laboratory data, as well as the desire to maintain professional boundaries by avoiding after-hours alerts on personal devices.

Approximately 50% of participants supported having the dashboard publicly displayed within the lab e.g. on a wall-mounted screen, so all staff can monitor live TAT data throughout the day.

When asked about notifications, most participants felt that on-dashboard alerts were sufficient for daily use. Alerts should be based on thresholds set according to the type of test and priority. Frequent alerts, such as emails for each threshold breach, were seen as excessive, particularly during periods of predictable delays (e.g. due to external disruptions). Instead, users preferred summary alerts or customisable triggers that balance oversight with practicality.

3.2.2.4 Perceived Benefits of the Dashboard

The value of the dashboard as a managerial and strategic tool was strongly emphasised by participants. It would enable the monitoring of trends related to workload distribution, staff scheduling, and stock management, supporting more informed operational decisions.

From an operational perspective, the dashboard could allow for real-time identification and resolution of delays, improving workflow efficiency and optimising resource allocation.

In terms of quality management, the tool could enhance KPI tracking, process traceability, and support continuous quality improvement efforts. Ultimately, this would contribute to better patient care through more timely and reliable laboratory services.

3.2.2.5 Prototype Feedback

All participants provided positive feedback on the overall layout and clarity of information presented in the prototype. The *workload versus test requests* feature was particularly valued, as participants noted its potential for identifying imbalances in workload distribution. The clear separation of pre-analytical, analytical, and post-analytical TAT also received favourable comments, since this breakdown is not commonly reviewed from a laboratory management perspective. However, some participants felt that the statistical detail should be revised, and they expressed a preference for displaying the median TAT alongside the target, supplemented with indicators showing

results exceeding 1.5× and 2× the target TAT. It was also noted that the prototype lacked specific data visualisations to highlight individual samples that exceeded the target TAT, which participants felt would be a valuable addition for identifying and investigating delays.

3.2.3 Requirements Specification

This section outlines the core system requirements for developing the TAT monitoring tool. The requirements are derived from the interview findings outlined in *Section* 3.2.2 Interview Key Findings, and reflect the particular needs, challenges and expectations of the participants. These requirements aim to support real-time monitoring, proactive decision-making, and improved laboratory efficiency through a centralised, accessible, and user-friendly dashboard. Requirements are categorised as functional, non-functional, data-related, and user-informed, ensuring a holistic foundation for system design.

3.2.3.1 Functional Requirements

The functional requirements represent core functions that must be delivered to achieve the system's purpose. The dashboard shall:

- display both real-time and historical TAT data.
- support data filtering by test type, date/time range, urgency (urgent/routine), and requesting department or ward.
- calculate and display the following TAT metrics: median TAT, percentage of tests within/outside set targets, TAT by testing phase, and hourly workload.
- visually highlight delayed samples using a traffic light colour-coding system.
- Show real-time alerts for overdue samples based on configurable thresholds.
- present trends in TAT performance over time using line and bar charts.
- display the current workload and status of pending samples.
- support exporting summary reports
- auto-refresh at configurable time intervals (e.g., every hour).

3.2.3.2 Non-Functional Requirements

The non-functional requirements define the performance characteristics of the system. For the TAT dashboard, this shall

- be accessible via desktop; mobile access is optional
- be intuitive, requiring minimal training.
- auto-refresh data without requiring manual input.
- Maintain optimal responsiveness and performance while handling large volumes of data
- support integration with the existing LIS platform

3.2.3.3 Data Requirements

Data requirements define the type, structure and frequency of data that the system must handle. The TAT dashboard shall:

- extract data from the LIS at periodic e.g. hourly intervals.
- TAT calculations shall be performed at the individual test level, not at the sample level, to avoid inaccuracies caused by late-added tests.
- capture the following data fields: test name, collection time, reception time, resulting time, authorisation time, priority, and requesting location.
- Data must be stored in a structured format suitable for analysis for both live data and periodic reporting.

3.3 System Architecture

The proposed TAT Dashboard system architecture is designed to enable the automated extraction, processing and visualisation of laboratory TAT data in real time. The system would integrate with the LIS as the primary source of data. The architecture would be comprised of a 4-layered approach: the data source layer, data integration layer, data processing layer and application backend, and user interface layer. All these layers are described in detail in the following section.

3.3.1 Data Source Layer

For the proposed dashboard, the primary data source would be the Laboratory Information System (LIS). The LIS records and stores different process timestamps, test data, and request details such as requesting ward information.

3.3.2 Data Integration Layer

Data for the relevant fields is extracted using a business intelligence software such as CorVu, which allows SQL querying on the LIS database. This data is retrieved at regular intervals, e.g., every hour, to refresh the live data.

3.3.3 Application Backend

Data is cleaned and transformed at the application backend. Core calculations such as TAT medians, % within targets and workload trends are also performed at the backend using coding within the application (Power BI). Data is also transformed in preparation for visualisations. Filters are set up to allow users to filter through data, and visualisations are set according to best practices, allowing the visualisations of filtered data.

3.3.4 User Interface Layer

The user interface allows the user to interact with the dashboard. The user can interact with the data through filters such as date, test name, priority and requesting department. The user can view statistics and trends through different visualisations, with real-time alerts on the dashboard. Some visualisations also allow user interactions to drill down on data. Data from the dashboard can also be exported as a PDF for statistical record-keeping.

4 Implementation

4.1 Introduction

This chapter describes the practical implementation of the Turnaround Time (TAT) Dashboard developed for monitoring and improving the performance of blood test workflows within the hospital laboratory setting. This chapter translates the user-informed requirements, functional specifications, and architectural design—outlined in the previous chapter—into a working system that can be deployed and evaluated in a real-world environment.

4.2 Development Environment and Tools

For the development of the TAT Dashboard a range of tools were used for data exploration, transformation, visualisation, and deployment. Jupyter Notebook was initially used to explore and understand the structure of the data extracted from the LIS. Python libraries such as pandas were used to identify key fields and to test preliminary TAT calculations.

To develop the dashboard, a range of business intelligence and dashboard platforms are available, such as Power BI, Tableau [78], and Python-based frameworks such as Dash [79]. Microsoft Power BI was selected for this project for several reasons. Firstly, the Microsoft portfolio is already part of Mater Dei Hospital's IT ecosystem, so the use of a Microsoft tool would ensure a smooth deployment and compatibility within the institution. Power BI also has strong capabilities in interactive visualisation, robust data modelling, and seamless integration with Comma Separated Values (CSV) based data sources [80].

Power BI is able to handle large volumes of data efficiently, even in high-throughput laboratory environments. Its in-memory storage, columnar data model, and data compression engine allow for fast querying and visual responsiveness, even when working with datasets exceeding 100,000 records [81, 82]. Additionally, Power BI supports secure deployment through Power BI Service, where the final dashboard could be published to the hospital's internal workspace. This enables users' full interaction with filters and slicers, while

restricting the ability to modify visuals or report structure. Thus, Power BI offers a good solution that aligns well with the existing hospital IT structure, enabling enhanced data visibility and decision-making.

Data was ingested to Power BI from CSV files generated via LIS exports, which would in a real-world application, be configured to update automatically periodically. Power Query was used for data transformation tasks such as cleaning timestamps, formatting fields, and filtering, while Data Analysis Expressions (DAX) was employed to compute key indicators, including median TAT, percentage within target, workload distributions, and alert thresholds [83, 84].

4.3 Data Preparation and Transformation

4.3.1 Data Acquisition

The dataset used in this project was obtained through an intermediary from the Pathology Department at Mater Dei Hospital, Msida, Malta. The dataset was compiled by a query using the iLAB APEX CorVu software, on iLAB APEX database (LIS database). The query was for blood test orders sent to the Pathology Department from January to April 2025, and the different timestamps associated with those orders.

4.3.2 Data Governance and Protection

The dataset used in this study was limited to process-related timestamps. No patient identifiers, demographic details, clinical information, or sample numbers were included. This approach ensured that best practice data handling principles were followed such as:

a. Data minimisation – only fields strictly required for turnaround time (TAT) analysis were extracted.
b. De-identification – timestamps were not linkable to patients, clinicians, or laboratory staff.

a. Secure storage – the dataset was provided through the authorised MDH intermediary. All data collected was stored on one personal computer for the duration of the project.
b. Restricted access – only the researcher and supervisor had access to the data collected.

4.3.2 Description of Dataset

The data collected was provided as four different datasets, one for each month. Python in Jupyter Notebook was used to combine and explore the dataset features. The combined dataset contained 6,637,367 entries having 343 unique Test Codes. Table 1 shows the Jupyter Notebook output for the data fields that were collected.

Table 1 Data Fields in the Dataset

	count	unique	top	\
'Test_code'	6637367	343	'NA'	
'Test_Expansion'	6637367	337	'Haemolysis Value'	
'Order_Priority'	6637019	2	'Routine'	
'Collection_Date'	6637360	128	12-Mar-2025 00:00:00	
'Collection_Time'	6637367	1440	31-Dec-1899 08:00:00	
'Receive_Date'	6637367	118	12-Apr-2025 00:00:00	
'Receive_Time'	6637367	1449	31-Dec-1899 12:08:00	
'Date_Resulted'	6606396	118	25-Jan-2025 00:00:00	
'Time_Resulted'	6606396	67576	31-Dec-1899 11:46:43	
'Date_Current_Status_Achieved'	6637367	118	05-Mar-2025 00:00:00	
'Time_Current_Status_Achieved'	6637367	67072	31-Dec-1899 15:25:38	
'Current_Status'	6637367	23	'S000000'	
'Location_Code'	6637367	2466	'TOA'	
'Location_Description'	6637367	2448	'Ticket of Admission'	
'Discipline_Code'	6637367	1	'C'	
'Section_Code'	6637367	4	'R'	

The data fields collected are described below:

Test Code – This code is used by the Laboratory Information System to identify the test ordered by the clinician.

Test Expansion – Each test code has an associated expanded description describing the test ordered.

Order Priority – Tests ordered can have one of two order priorities, Routine or Urgent. The tests are flagged by the clinician as being requested as urgent or routine according to the type of test, and whether it's needed for routine testing or for more time-sensitive purposes. Tests ordered as urgent are given priority by the laboratory to be issued as soon as possible, usually within an hour e.g. a Troponin test is used to evaluate a suspected heart attack case, where immediate treatment is needed, and thus this test is always considered as an urgent test. A total cholesterol test, on the other hand, as part of a yearly checkup would be considered as a routine test and would be given second priority after urgent testing.

Current Status – Each test record is given a status code by the LIS according to the level of completeness of the test. The initial letter of the status can be as follows:

E – the test has been ordered but the result field is still empty

F – a result has been entered for the test, but the result has not been authorised/validated to be sent to iSOFT Clinical Manager (iCM)

N – a result has been technically authorised; the result has been reviewed but not sent to iCM

S – the result has been authorised (clinically validated) and can now be viewed by clinicians on iCM

The status letter is followed by a digital code that is used to differentiate between different occurrences for the same status. E.g. if a test is resulted the code is F000000, but if the test is repeated and the second result is imputed, the status changes to F020000 to indicate that there was a change. Each digit represents a different type of change in the result.

Collection Date, Collection Time – This is the date when the blood sample was collected. After the clinician places an order for a test through the iSOFT Clinical Manager, a barcode label is generated and printed when the blood sample is collected, to be affixed to the sample container. At the time of printing of this barcode label, the collection date and collection time are populated in the Laboratory Information System.

Received Date, Received Time – On receipt of the sample to the Pathology reception, the sample is scanned through a specific module on the LIS, where the sample is marked as received by the department, which information is relayed to the iCM. On scanning, the date and time are recorded as the received date and time. This process can be done manually or through an automated sorter.

Date Resulted, Time Resulted – The LIS logs the date and time that a result has been entered in the result field (result status is 'F').

Date Current Status Achieved, Time Current Status Achieved – This time reflects the last timestamp for when a test status was changed. In the case of tests that have been authorised to be released to iCM, this date/time is the time that the result was changed to status 'S'. However for results that have been entered but not authorised, this date/time reflects the last change to status 'F' or 'N'.

Location Code – Each order has an assigned code according to where the order originated from, i.e. specific wards, clinics, outpatients, private clinics or other hospitals. All locations have specific codes assigned to them.

Location Description – Each location code has an associated expanded description describing the location.

Discipline Code, **Section Code** – These code refers to the department for which that specific test is assigned to.

4.3.3 Dataset Challenges

Laboratory Information Systems (LIS) are crucial for managing diagnostic workflows, but they often present challenges when used for secondary purposes such as performance dashboards and quality monitoring. LIS platforms are designed for transactional efficiency and may lack the structure and standardisation needed for robust data analysis.

Common issues include inconsistent data entry, missing or duplicate records, varying processes between departments, and timestamp variability for key

process steps such as sample receipt, testing, and result release. These challenges complicate the calculation of performance metrics like turnaround time (TAT) and hinder cross-departmental comparisons. Understanding and addressing these dataset-related issues is critical for ensuring that the dashboard accurately reflects laboratory performance metrics, such as turnaround time (TAT), and provides actionable insights to stakeholders.

The following section outlines the most common data-related challenges encountered when working with LIS datasets, with particular focus on their implications for dashboard design and implementation.

4.3.3.1 Data Integrity

Data integrity refers to the accuracy, completeness, and consistency of data. For the TAT Dashboard, which relies on Laboratory Information System (LIS) extracts, integrity issues can arise from missing timestamps, misclassified priorities, duplicate entries, or manual entry errors. Such problems can distort turnaround time calculations and affect the reliability of reported performance metrics. Ensuring data integrity through validation checks and cleaning is therefore critical to producing trustworthy insights.

4.3.3.1.1 Temporal inaccuracies

Accurate evaluation of TAT analysis relies heavily on precise and reliable timestamps recorded at each stage of the laboratory testing process. However, several practices can introduce inconsistencies in these timestamps, potentially skewing TAT metrics. For instance, the blood collection timestamp is automatically recorded when the clinician prints the barcode label before blood-letting. However, test requests from locations outside the main hospital may require manual data entry. These orders are manually inputted on receipt, and thus the collection and receipt time are recorded with the same timestamp, which does not reflect actual practice. These manual processes may also mean that data entry is batched, and there is a delay in inputting these orders.

Another challenge in the dataset was the presence of system-induced inaccuracies in time-related fields. Multiple tests had the fields for resulted date and time equal to the time that the test was authorised to status S. This

would happen in cases where specific tests are processed through a middleware software which is interfaced directly with the LIS. The result is processed by the scientist through the middleware, which then sends the result to the LIS. The LIS is setup to clinically validate such results automatically on transmission from the middleware. Thus, when analysing data for these tests, the post-analytical phase would misleadingly be calculated as 0 minutes. This complicates accurate analysis of TAT times especially for the analytical and post-analytical phases and thus data from the middleware would be more appropriate to analyse these phases for these tests.

When using automated systems that are directly interfaced to the LIS, results are automatically sent to LIS as soon as they are available from the analyser. However, for other testing requiring manual analysis, result data is inputted manually in the LIS. Therefore, there may be delays between the end of the analytical phase and when the scientist actually enters the results manually in the LIS. In this case, the 'Resulted' timestamp may not reflect the true chronology of events.

These discrepancies can affect the interpretation of performance indicators and must be considered when drawing conclusions from TAT data.

4.3.3.2 Data Formatting

Each timestamp in the dataset is stored as separate date and time columns. The date column has a date time format with the correct date and '00:00:00' time, whilst the time column has a '31/12/1899' date and the correct time (Figure 8). This poses a challenge, as calculations cannot be performed directly on this data and each timestamp must be pre-processed to combine the columns for the true date/time combination, before further analysis.

Test_code	Test_Expansion	Order_Priority	Collection_Date	Collection_Time	Receive_Date	Receive_Time	Date_Resulted
NA	Sodium (Serum)	Routine	18-Jan-2024 00:00:00	*31/12/1899 03:36:00*	*18/01/2024 00:00:00*	*31/12/1899 03:36:00*	*18/01/2024 00:00:00*
NA	Sodium (Serum)	Routine	18-Jan-2024 00:00:00	*31/12/1899 03:55:00*	*18/01/2024 00:00:00*	*31/12/1899 06:32:00*	*18/01/2024 00:00:00*
NA	Sodium (Serum)	Routine	18-Jan-2024 00:00:00	*31/12/1899 03:59:00*	*18/01/2024 00:00:00*	*31/12/1899 06:31:00*	*18/01/2024 00:00:00*
NA	Sodium (Serum)	Routine	18-Jan-2024 00:00:00	*31/12/1899 04:49:00*	*18/01/2024 00:00:00*	*31/12/1899 04:49:00*	*18/01/2024 00:00:00*

Figure 8 Date/Time Formatting in Dataset

4.3.3.3 Field Ambiguity

The dataset contains the fields 'Date Current Status Achieved' and 'Time Current Status Achieved'. This data for this field is ambiguous on its own, as the timings may refer to different statuses of the test, depending on the current status of the test. Therefore this data must be interpreted depending on the data in the field 'Current status' Although each status has a timestamp in a separate field e.g. Collection Date/Time for status E, Resulted Date/Time for status F, there is no specific field for final status 'S' and thus the field of 'Current Status Achieved Date/Time' must be used for the tests that are in status 'S'. Since this column contains mixed date/time data according to the status of the test, data must be pre-processed to filter by status when using this field in different TAT calculations to avoid misleading metrics.

4.3.4 Data Cleaning and Transformation Procedures

Before analysis and dashboard development, it was essential to ensure that the dataset was accurate, consistent, and analytically meaningful. Raw laboratory data extracted from the LIS often contains inconsistencies such as missing values and incorrect timestamp formats. Without appropriate cleaning, such anomalies can distort statistical measures and lead to misleading conclusions.

The data cleaning process in this study aimed to retain all records for traceability while ensuring that calculations reflected only valid and reliable entries. Rows with incomplete or invalid timestamps were preserved in the dataset for quality monitoring but excluded from total TAT computations. This approach allowed tests lacking one or more timestamps to be included in pre-analytical and analytical time calculations, while preventing them from distorting overall performance indicators.

Transformation procedures were applied to standardise data formats, derive new analytical fields, and prepare the dataset for integration into the visualisation tools. These steps included converting timestamp fields to a consistent datetime format, calculating TAT for each phase of the total testing process, and generating service-level agreement (SLA) compliance indicators — measures that identify whether each test met predefined turnaround time targets agreed between the laboratory and its stakeholders.

Most metrics were based on the aTAT (time from sample ordering to result authorisation/release), also referred to as the in-lab TAT, as the interview participants identified this metric as the most useful, since it is the TAT that reflects the whole lab process.

4.3.4.2 Cleaning Missing Timestamps

Missing timestamps in the dataset were cleaned by assigning a 'null' value. This prevents missing data, from distorting calculation results in total TAT calculations. Power Query (M language) was used to clean these fields before loading data into the model, as follows:

```
    #"Cleaned Date Columns" = Table.TransformColumns(
        #"Promoted Headers",
        {
            {"Collection_Date", each try
DateTime.FromText(_) otherwise null, type datetime},
            {"Collection_Time", each try
DateTime.FromText(_) otherwise null, type datetime},
            {"Receive_Date", each try
DateTime.FromText(_) otherwise null, type datetime},
            {"Receive_Time", each try
DateTime.FromText(_) otherwise null, type datetime},

            {"Date_Resulted", each try
DateTime.FromText(_) otherwise null, type datetime},

            {"Time_Resulted", each try
DateTime.FromText(_) otherwise null, type datetime},

            {"Date_Current_Status_Achieved", each try
DateTime.FromText(_) otherwise null, type datetime},

            {"Time_Current_Status_Achieved", each try
DateTime.FromText(_) otherwise null, type datetime}

        }

    ),
```

4.3.4.4 Calculated Columns and Measures

Calculated columns in Power BI are custom columns created using Data Analysis Expressions (DAX) to extend the dataset beyond the raw data. In this study, they were used to calculate turnaround times (TAT) for each entry, for each testing phase, and classify records by data validity. Many calculated fields were created; examples of which are described below.

Measures within Power BI are designed for aggregations or summarised results, such as averages, medians, counts, or SLA compliance percentages. They are context-dependent, meaning their results change depending on the filters and dimensions applied in the report.

4.3.4.4.1 Formatting Date and Time Fields

In the raw dataset, date and time were stored in separate columns, but each also contained default values from the other field. The date column included a default time value of 00:00:00, while the time column contained a default date of 31/12/1899. To obtain the actual timestamps for analysis, these columns were first cleaned and then recombined into a single datetime field. The following DAX formula was used to merge the date and time columns in preparation for subsequent calculations:

```
Collection DateTime = DATE(YEAR([Collection_Date]),
MONTH([Collection_Date]), DAY([Collection_Date])) +
TIME(HOUR([Collection_Time]),
MINUTE([Collection_Time]), SECOND([Collection_Time]))
```

4.3.4.4.2 Time Bins

In preparation for visualisations in the final dashboard, some data had to be categorised into bins e.g. sample collection times were categorised using hourly bins to be able to visualise workload distribution across different times of day. This transformation enabled aggregation and plotting of sample volumes per hour, revealing temporal patterns in laboratory workload. This binning was performed by extracting the hour component from each timestamp to a new column using this DAX code:

```
RecievedHour = HOUR([Receive DateTime])
```

This allowed the generation of time-based workload graphs, such as histograms or line plots, showing the number of samples collected during each hour of the day. These visualisations help identify peak collection periods and inform staffing or workflow optimisation.

4.3.4.4.3 Status Bins

The Current Status field entries were also binned according to the first character of the status (E,F,N or S), irrespective of the subsequent characters (see 4.3.2

Description of Dataset). This would also help to filter the entries by status type for visualisations and calculations.

```
Current Status Letter = LEFT('TAT Data'[Current_Status], 1)
```

4.3.4.4.4 Timestamp Field Ambiguity

In order to address the field ambiguity issue discussed in Section 4.3.3.3 Field Ambiguity, each measure that is introduced using the last timestamp (result release) has to be filtered by status, as the timestamp for last status achieved may not always refer to the 'S' status. Instead of addressing this issue with each expression that is introduced, another column was created, populating the timestamp in cases where the status is 'S' and leaving the cell as blank/null for other statuses, excluding them from calculations. This field would then be used directly in the expressions.

```
Authorised DateTime =
IF ( 'TAT Data'[Current Status Letter] = "S", 'TAT Data'[CurrentStatus DateTime], BLANK() )
```

4.3.4.4.5 Calculating TAT phases

For each data entry, calculations were carried out for each phase of the testing process. Timestamps were used in calculations, and new columns were created for each analytic. The total testing TAT, pre-analytical, analytical and post-analytical phases were populated as follows:

e.g. Preanalytical phase DAX formula

```
Preanalytical = DATEDIFF([Collection DateTime], [Receive DateTime], MINUTE)
```

4.3.4.4.6 aTAT Category

Each data record was categorised to establish whether that particular record has exceeded the aTAT. This was done in preparation for the visualisation of counts of the number of entries within target aTAT, within 1.5x of target aTAT and within 2x of target aTAT. The categorisation depends on the targets set for

each test according to whether it is an urgent or a routine order. These targets were set in a separate table in Power BI, which was linked in the model with the TAT data source.

```
aTAT Category =
VAR _actual = 'TAT Data'[Analytical] + 'TAT
Data'[Postanalytical]
VAR _priority = 'TAT Data'[Order_Priority]
VAR _test = 'TAT Data'[Test_code]
VAR _target =
    SWITCH(
        _priority,
        "Routine",
VALUE(LOOKUPVALUE('TestCodes'[Cut off TAT
Routine], 'TestCodes'[Test_Code], _test)),
        "Urgent",
VALUE(LOOKUPVALUE('TestCodes'[Cut off TAT Urgent],
'TestCodes'[Test_Code], _test)),
        BLANK()
    )
RETURN
    SWITCH(
        TRUE(),
        _actual <= _target, "< Target aTAT",
        _actual <= _target * 1.5, "Within 1.5x
Target",
        _actual <= _target * 2.0, "Within 2x
Target",
        "Outliers"
    )
```

4.3.4.4.7 Calculating % Within Target aTAT

To calculate the percentage of records within the target aTAT, each record was first assigned a value of 1 if it met the target and 0 if it fell outside the target.

```
Within_aTAT =
VAR cutoff =
    SWITCH(
        'TAT Data'[Order_Priority],
        "Urgent", VALUE(RELATED('TestCodes'[Cut
off TAT Urgent])),
        "Routine", VALUE(RELATED('TestCodes'[Cut
off TAT Routine])),
        BLANK()
    )
VAR total_time =
```

```
    'TAT Data'[Analytical] + 'TAT
Data'[Postanalytical]
RETURN
IF(total_time <= cutoff, 1, 0)
```

A calculated measure was then used to calculate the percentage of records within target aTAT

```
% Within aTAT =
DIVIDE(
    SUM('TAT Data'[Within_aTAT]),
    COUNTROWS('TAT Data'),
    0
) * 100
```

4.3.4.4.8 Assigning Colour based on value

A calculated measure was created to assign red, yellow, or green (RYG) values based on the *"% Within aTAT"* metric, enabling traffic light–style alerts in the visualisations.

```
Colour % Within TAT =
IF(
    [% Within aTAT] >= 90, "#4CAF50",   // Green
if ≥ 90%
    IF(
        [% Within aTAT] >= 70, "#FFC107", // Amber
if 70–90%
        "#F44336"                       // Red if
< 70%
    )
)
```

4.4 Dashboard Construction

This section describes the process of constructing the dashboard, focusing on integrating the previously defined measures into suitable visualisations. The selection of chart types, layout design, and interactive elements to ensure that the dashboard supports effective monitoring of turnaround time trends are also described. The implementation also emphasises usability, with the graphical user interface (GUI) designed to be clear, and consistent with the functional and user requirements identified earlier.

4.4.1 Table Relationships

Python in Jupyter Notebook was used to extract all the unique test codes from the dataset. A table was created using these codes, assigning to each code; the laboratory section code where the test is analysed, the target aTAT for both urgent and routine priorities. This enables the generation of metrics using target values, specific to each test and priority, e.g. % of samples within target aTAT.

Another table was created with the laboratory section codes and their full description. This enables the implementation of filters using full laboratory names. The Power BI model view shown in Figure 9 shows the relationships between the created tables and the dataset.

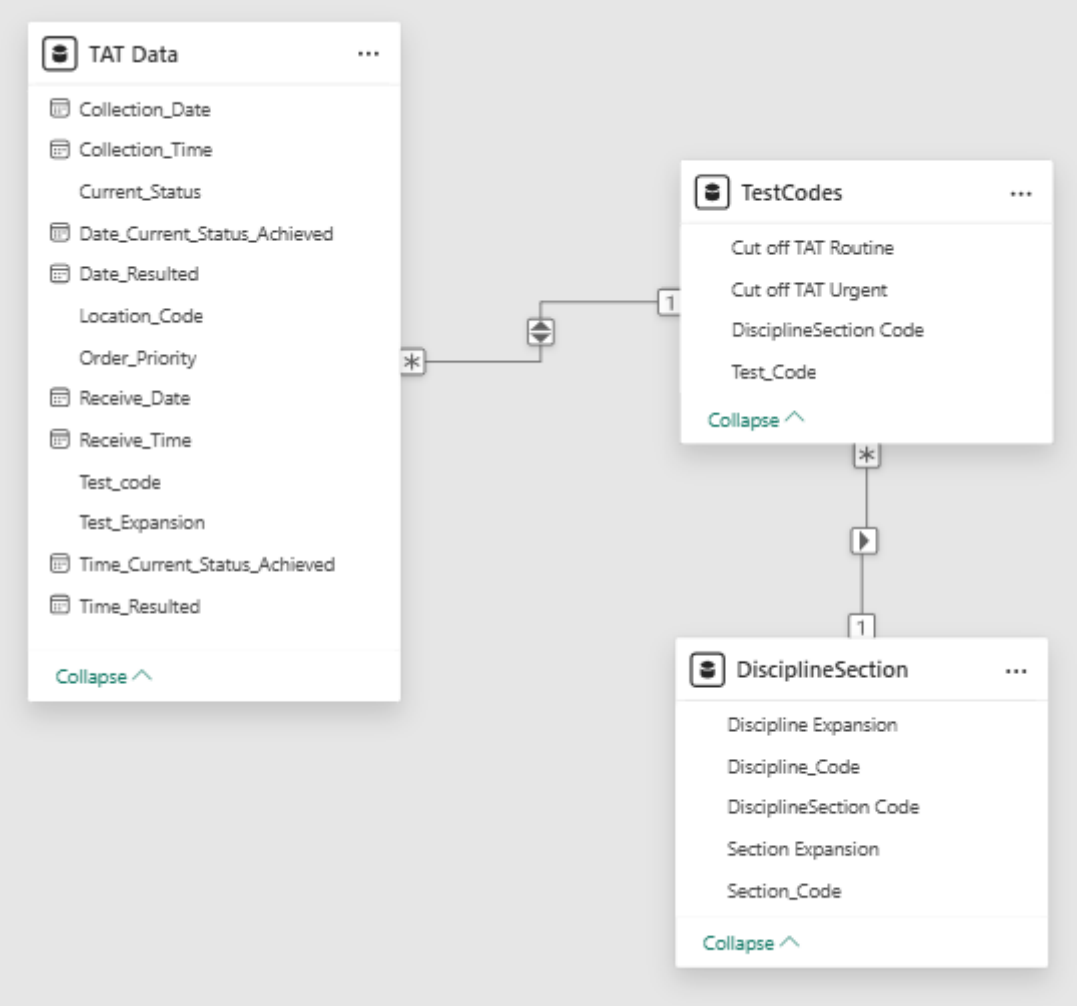


Figure 9 – Power BI Model View showing the table relationships.

4.4.2 Layout and Visualisations

The dashboard was designed by established usability principles, particularly Nielsen's usability heuristics, to promote clarity, efficiency, and intuitive navigation, as described in *Section 2.4.3 Key considerations in dashboard design* [85, 63, 59, 58, 86]. The layout followed a hierarchical structure, placing high-level data at the top and progressively more detailed visualisations further down. This enables users to initially see an overview before drilling down into specifics.

A clean and simple layout was maintained throughout, avoiding overwhelming the space with excessive information or unnecessary visual elements on a single screen. By maintaining a minimalist design, cognitive load is reduced, allowing the user to process the information being displayed better [58]. Numerical data were presented appropriately, with scaled numbers for easier reading, ensuring figures are clear to interpret.

The use of colour in the dashboard followed established data visualisation principles to ensure clarity, consistency, and accessibility. Colours were applied purposefully to convey meaning rather than for decorative purposes, to guide user attention and highlight important information. A restricted colour palette was implemented to reduce visual clutter that can distract from the message and impair interpretation [33].

The use of subtle outlines with shadows, around filters and visualisations, provided visual grouping and separation between elements, supporting the 'aesthetic and minimalist design' heuristic [58]. The use of subtle borders maintained structure without overwhelming the user, ensuring that elements were distinct while still part of a unified interface. To further improve readability, a white background with high-contrast text and visuals was used, which supports prolonged viewing without eye strain, critical for tools intended for regular operational use.

Visualisations were carefully matched to the type of data being presented e.g. gauges were used for KPIs which were compared to a target. Line charts were used for temporal trends, which allows users to interpret the data visually. Bar charts were used in favour of pie charts and doughnut charts as the latter are

difficult to interpret accurately by the human brain [63, 59, 64]. Detailed information, such as statistical breakdowns, was displayed as tables at the bottom of the dashboard. KPIs were selected according to the requirements gathering, relevant to both the dashboard's target audience and the organisation's operational objectives.

Data filters were positioned at the top of the dashboard. This placement was chosen to enhance the visibility of system status, ensuring that users can immediately see the current filtering parameters before interpreting the data [58]. This design choice also aligns with dashboard design best practices, which recommend that global controls be placed in high-visibility and predictable areas, such as a horizontal bar at the top. The top of the page is consistent with user scanning patterns, improving discoverability and reducing cognitive effort [87, 88, 89]. A dedicated *Reset Filters* button was included to facilitate a quick return to the default view, reducing the likelihood of users unintentionally applying conflicting filter combinations. This directly supports Nielsen's 'error prevention' heuristic [58], which emphasises designing interfaces to minimise the chance of user mistakes before they occur.

A calendar picker was used as an intuitive method for date selection. The timestamp for the last data refresh was prominently displayed, directly addressing the heuristic of 'visibility of system status' [58]. This was achieved by using an expression showing the latest timestamp:

```
Latest Date =
CALCULATE(
    MAX('TAT Data'[CurrentStatus DateTime]),
    REMOVEFILTERS('TAT Data')
)
```

Collectively, these design choices ensured the dashboard was visually accessible, operationally efficient, and aligned with recognised usability principles.

4.4.3 Interactivity and Graphical User Interface

As outlined in *Section 4.4.2 Layout and Visualisations*, the user interface was designed using heuristic principles and best practice guidelines to provide a visually clear, interactive and user-friendly environment. Filter controls were positioned strategically at the top of the dashboard, maximising visibility and encouraging their use [89].

Filters were included according to findings from the participant interviews for: Section, Test Name, Order Priority, Location of Order and Received Date.

A 'Reset Filters' option was implemented to quickly revert the view to default settings. Filters are visually grouped against a light background without borders, separating them from data visualisations while maintaining a clean aesthetic.

Beyond static summaries, the dashboard supports drill-down interactions, allowing users to click on specific data points, categories, or visual elements to reveal underlying details. For example, when selecting a date range, a bar chart is plotted for the median ATAT for each day in that date range. One can focus on one particular day by clicking on individual bars within the bar charts, changing the rest of the visuals in the dashboard to reflect that day's data (Figure 10). This layered interaction approach enables users to move seamlessly from macro-level performance insights to micro-level data exploration within the same environment.

A red–yellow–green (RYG) colour scheme was used for the KPI visuals, drawing on familiar colour associations where green represents on target performance, yellow indicates caution, and red highlights issues requiring attention. The colour red was also used in the table, highlighting specific sample tests that are over their target TAT. This enables users to recognise performance status instantly without conscious effort.

The developed second prototype described above addresses all the requirements outlined during participant interviews described in Section 3.2.3 Requirements Specification. The second prototype design and GUI can be seen in Figure 11.

4.4.4 Export of Periodical Reports

Users can easily export periodical reports as static files with the developed dashboard. Power BI provides options to export dashboards or report pages into formats such as PDF, allowing users to save a fixed version of the data for specific periods for record-keeping, distribution, or review. Even though the dashboard remains interactive for real-time and historical monitoring, static snapshots can be produced on demand, ensuring consistency with traditional reporting practices. The process can be done directly from the dashboard, making it straightforward to generate standardised reports for management or audit purposes without the need for additional tools.

[A]

[B]

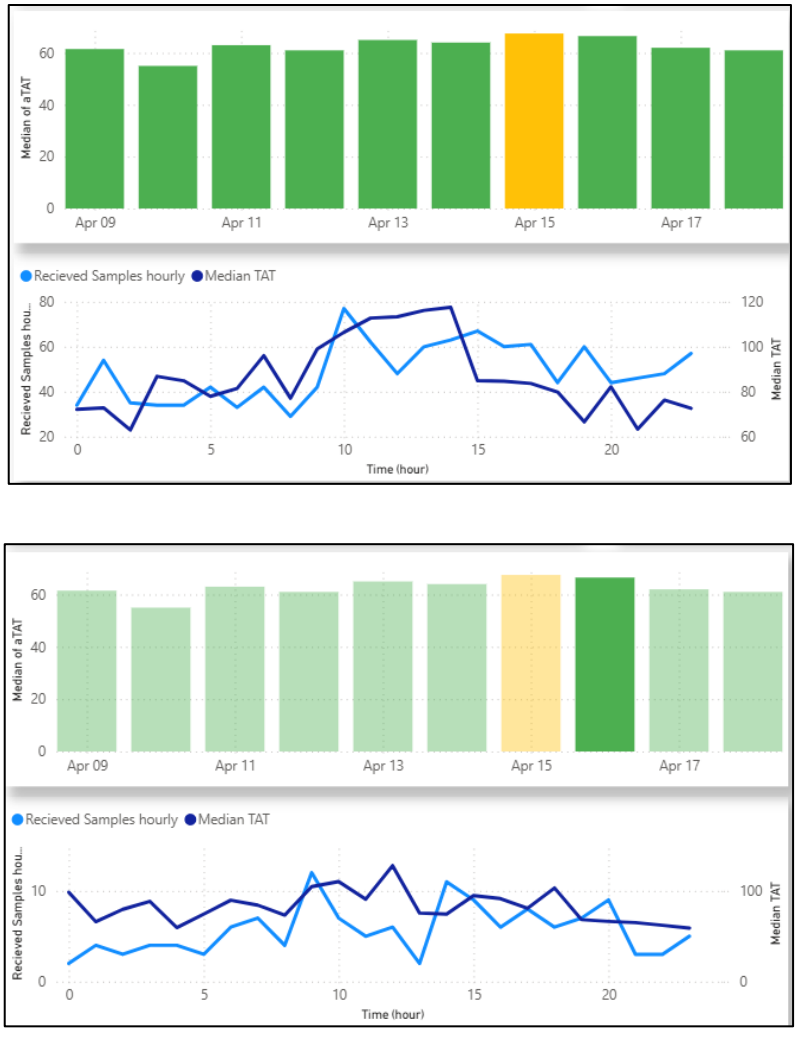


Figure 10: Example of interactive drill-down of data, [A] shows the data for the selected range of dates. [B] shows how the selection of 1 day from the date range (16th April) changes the 2nd graph to reflect data from that day only.

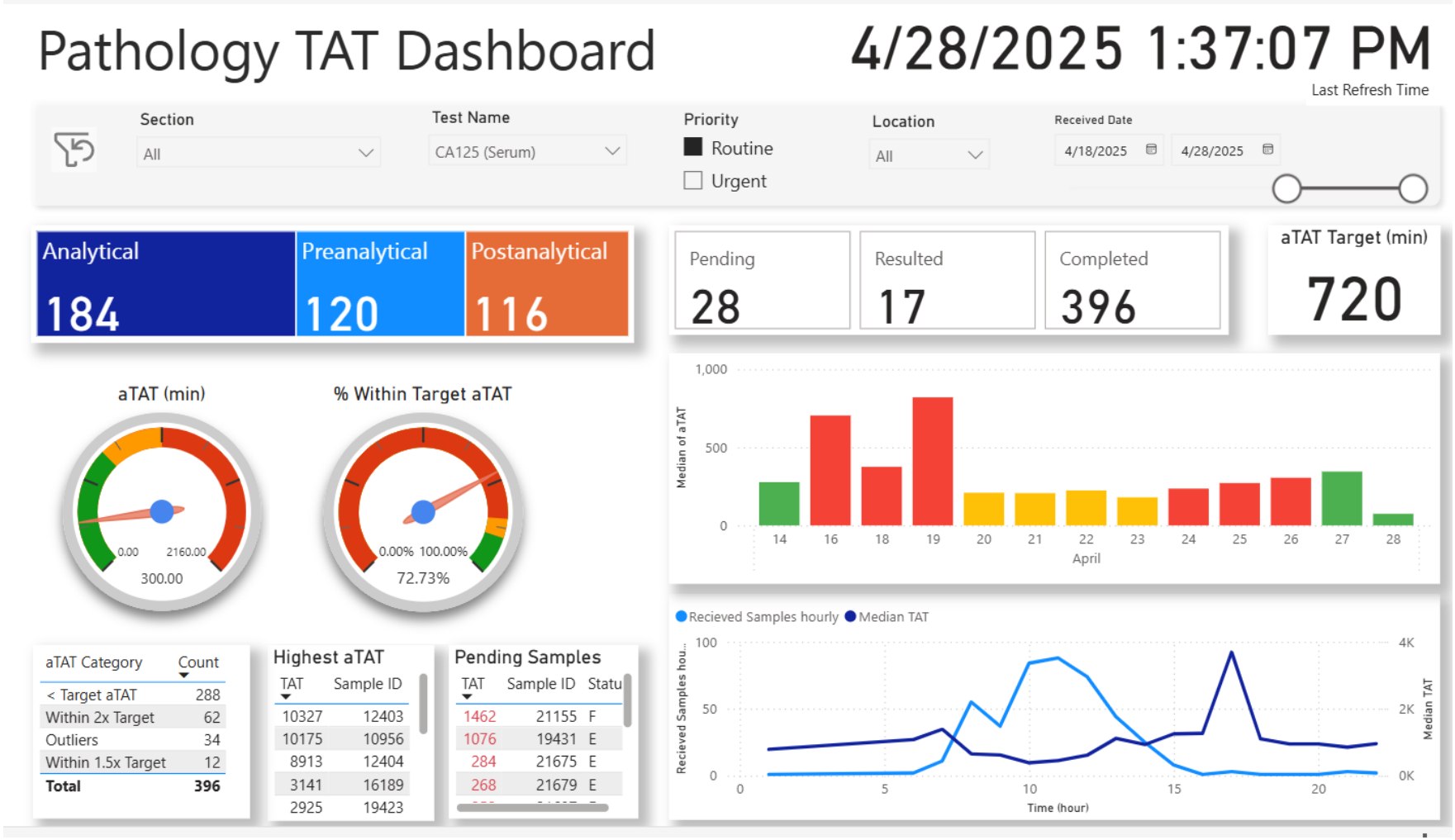


Figure 11 The second dashboard prototype as developed in Power BI after requirements gathering.

4.5 Deployment

The proposed TAT-monitoring solution is designed as a streamlined architecture intended for integration within the hospital's existing IT infrastructure. In practice, the Laboratory Information System (LIS) exports data as a CSV file periodically, e.g. every hour, with each file containing only new records from the preceding interval. This design ensures efficient ingestion and avoids performance delays associated with querying large cumulative datasets. All incoming files are transferred to and stored on a secure hospital server, which functions as the central repository where successive updates are consolidated and structured around specimen identifiers. Each new batch of records is compared against existing entries: if a matching record already exists, it is updated with the most complete information; if it is new, it is appended. This process maintains a comprehensive dataset while preventing duplication and reducing query times.

Due to strict security measures governing hospital servers, these processes could not be demonstrated directly in the present study. Instead, the proof of concept was conducted on static data extracted from the LIS. Dashboards in Power BI were populated from these static files to illustrate the intended functionality, while in a live environment, automated refreshes would be scheduled in alignment with the LIS export cycle. In Power BI Desktop, data can also be refreshed manually at any time by selecting the Refresh button to reload the latest records.

User access is provisioned through the organization's corporate authentication system. The dashboard is shared only with registered corporate accounts, ensuring that access is both secure and consistent with hospital IT governance policies. By leveraging existing identity infrastructure, the solution avoids separate account management and maintains alignment with institutional data security standards.

5 Evaluation

This chapter assesses the extent to which the developed solution fulfils its intended purpose. The evaluation is conducted through usability testing, in which representative users interact with the system for the first time to complete predefined tasks, allowing assessment of its intuitiveness and ease of use. In addition, user feedback is gathered through a standardised questionnaire, providing quantitative scores and qualitative insights to evaluate overall system performance and user satisfaction.

5.1 Usability Study

A usability study examines how effectively and efficiently real users can interact with a system and evaluates the user's software experience and satisfaction.

Within literature, usability is typically described in terms of learnability, efficiency, memorability, error prevention and recovery, and satisfaction [90]. To evaluate these dimensions, representative users are observed performing realistic, goal-oriented tasks, while both quantitative measures e.g., task completion rates and qualitative insights e.g., observational notes, user feedback are collected.

5.1.1 Participant Selection

The usability testing involved six participants, all of whom were laboratory managers who had previously contributed to the requirements gathering phase of this project. Their inclusion ensured that the evaluation reflected the perspectives of stakeholders with both operational oversight and direct familiarity with laboratory workflows.

These participants were selected for their:

- relevant domain expertise in clinical laboratory operations.
- Decision-making roles, which often require reviewing TAT metrics for quality management.

- Prior involvement in identifying system requirements, giving them an informed perspective on whether the developed dashboard met its intended goals.

By engaging this group, the usability testing captured feedback from individuals who not only represent key end users but also have the authority to influence dashboard adoption and integration into existing quality processes.

A widely cited heuristic in usability research suggests that testing with five participants per iteration can uncover approximately 85% of a system's usability problems [91]. This is based on the principle of diminishing returns, whereby the likelihood of discovering new issues decreases sharply after the first few participants [92]. Therefore, the use of 6 participants for this evaluation would be expected to reveal the majority of usability issues of the system.

5.1.2 Design of Usability study

The usability study was designed to assess the intuitiveness of the TAT Dashboard across its core functionalities, while evaluating participants' ability to complete a range of tasks accurately and provide the specific information requested. The study aimed to replicate realistic usage scenarios to observe how effectively and efficiently users could interact with the system without step-by-step guidance (Appendix D: Usability Study Sheet).

Each participant was given access to the dashboard and provided with an instruction sheet outlining seven tasks. These tasks were selected to cover a representative range of dashboard operations, including retrieving specific metrics, interpreting visual indicators, applying and resetting filters, and identifying data values. Rather than providing explicit, step-by-step guidance, the instructions encouraged users to explore the application's functions independently.

Performance was measured using both quantitative and qualitative methods. Quantitative measures included task completion accuracy, self-reported confidence ratings on a five-point scale, ease-of-finding assessments for each

task, and a System Usability Scale (SUS) questionnaire (Appendix E: SUS Questionnaire for TAT Dashboard) [93] . Qualitative feedback was gathered through observational notes during task execution and post-test comments, capturing difficulties, navigation patterns, and user feedback.

This design ensured that the usability study provided a balanced evaluation, identifying both strengths in the dashboard's design and specific areas where refinements could enhance accuracy, efficiency, and user satisfaction.

5.2 Usability Testing Results

5.2.1 Task Completion and Accuracy

The task completion results indicate that the TAT Dashboard demonstrates generally good usability, particularly for straightforward queries. Tasks 1 (identifying the latest data refresh time), 4 (percentage of urgent calcium samples within target), and 7 (counting samples received at a specific time) achieved 100% accuracy, confirming that both simple single-step lookups and certain percentage-based performance queries were clear and easy to execute.

Task 3 (reset all filters) revealed an interesting usability behaviour: although all participants ultimately cleared the dashboard filters successfully, half of them did so by manually resetting each filter individually rather than using the dedicated "Reset All Filters" button. All participants took noticeably longer to complete this task, suggesting that the button's placement or visual prominence may need improvement. While this did not prevent task completion, it indicates that efficiency and discoverability could be enhanced for this function.

Lower accuracy rates were observed for Tasks 2, 5, and 6, which involved multi-step filtering and data interpretation. Task 2 (aTAT for Troponin T) achieved 50% accuracy, likely reflecting early-stage unfamiliarity with filter operations, as it was the first task requiring direct manipulation of dashboard controls. Task 6 (aTAT for routine Albumin tests) showed 33.3% accuracy, with most errors traced to the wrong filter being applied. This could be due to

the user not resetting the filters from previous tasks, influencing the final answer. Task 5 (highest aTAT for Albumin) recorded no correct responses, with all users giving different answers. This suggests that the users were not looking at the correct metric, and the table showing the highest TATs may require better labelling and visual highlighting.

As part of the usability study, participants were asked whether the gauge graphics used to visualise performance metrics were easy to understand. All participants responded positively, confirming that this visualisation approach was both clear and effective for conveying percentage-based performance data. This clarity was further demonstrated by the 100% accuracy achieved in Task 4, which required interpreting a gauge display.

From a usability perspective, these results do not indicate poor overall usability. Instead, they highlight specific functional areas where interface clarity, filter labelling, and data presentation could be enhanced to reduce error rates for analytical tasks.

5.2.2 Confidence Ratings Analysis

Participant self-ratings of confidence, measured on a five-point Likert scale (1 = not confident, 5 = very confident), indicated generally high assurance in completing the assigned tasks. The mean confidence scores for all tasks exceeded 4.0, with Question 1 (identifying the latest data refresh time) achieving a perfect mean score of 5.0, suggesting the task was universally straightforward.

Slightly lower mean scores were recorded for Question 2 (mean = 4.17) and Question 6 (mean = 4.50), where some participants rated their confidence as low as 3. These questions required users to find particular statistics through the use of filters, which required more effort, and may be less immediately intuitive than other tasks. Notably, Question 2 was the first task requiring direct user interaction with the dashboard, and participants may have felt less confident in their responses as they were still becoming familiar with the interface. This trend is supported by the observation that confidence ratings increased for all subsequent questions, suggesting that familiarity with the tool improved user assurance over time.

Tasks related to interpreting performance metrics—Questions 4 and 5—recorded consistent high means of 4.67, reflecting solid user confidence but highlighting potential for minor improvements in metric presentation or navigational clarity.

Overall, these results support the conclusion that the dashboard is generally intuitive and effective for its intended audience, with only a few task types presenting opportunities for refinement in future iterations.

5.2.3 Ease of Finding Information

Participant feedback on whether task-related information was easy to locate showed generally strong performance, with most tasks receiving very high ratings. Tasks 1, 4, and 5 achieved 100% positive responses. These results align with the 100% accuracy rates observed for Tasks 1 and 4 in the task performance analysis and reinforce the earlier finding that the gauge visualisations used in percentage-based displays were clear and effective for all participants.

In contrast, Task 2 (aTAT for Troponin T) scored the lowest, with only 50% of participants indicating the information was easy to find. This mirrors the 50% accuracy rate and lower confidence scores recorded for the same task, suggesting that initial filter use posed a barrier for some users, particularly since this was the first filter-based task attempted.

Task 3 (reset all filters) received a 66.7% positive rating, which is consistent with the observed behaviour where half of the participants opted to reset filters individually rather than using the dedicated “Reset All Filters” button. This suggests that while the result could still be achieved, the discoverability of this function could be improved to enhance efficiency.

Overall, these ease-of-finding results are consistent with the broader evaluation trends: simple lookups and visualised metrics were highly successful, while tasks requiring multi-step filtering were more prone to uncertainty, reduced confidence, and errors.

5.2.3 System Usability Score

The System Usability Scale (SUS) score was calculated from the questionnaires (Appendix Appendix E: SUS Questionnaire for TAT Dashboard), with a result of 82.9, which is considered well above average in comparison to standard usability benchmarks [93, 94]. This score places the dashboard firmly in the "good" usability range, well above the average benchmark, but just below the "excellent" threshold of 85 established by Bangor et al. (Figure 12) [94].

High SUS scores have also been associated with increased adoption likelihood and user satisfaction [93]. Given that the dashboard's SUS score approaches the upper end of the scale, these findings indicate strong acceptance potential among target users. The strong performance aligns with high task completion and confidence ratings, though there remains a small margin of further improvement toward truly outstanding usability.

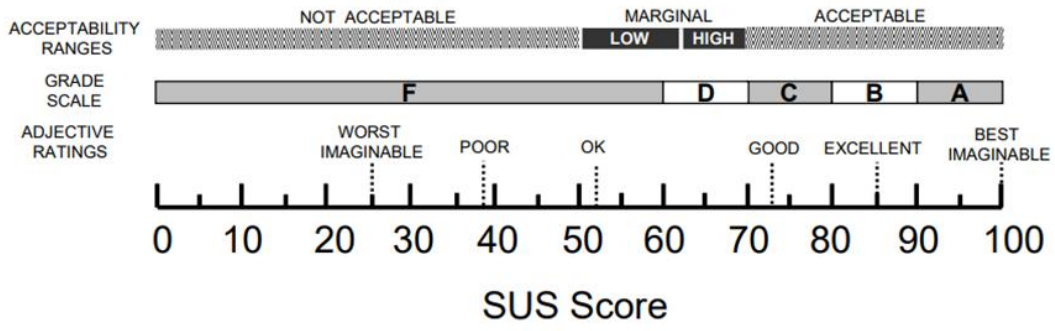


Figure 12 A comparison of the adjective ratings, acceptability scores, and school grading scales in relation to the average SUS score. Source: [94]

5.2.4 Other Feedback

Participants were invited to provide open-ended feedback, which highlighted several areas for improvement. Firstly, for the filters, a search option was suggested, especially for the Test Name field, which is quite extensive in options. A clearer explanation is required regarding the meaning of the data labelled *Analytical, Pre-analytical,* and *Post-analytical*. Additionally, the labelling of this section was noted to be partially obscured due to limited display space and should therefore be adjusted for improved visibility. For the tables displaying the highest TAT values and pending samples, participants suggested that the fields be rearranged so that the *Sample ID* appears before

the aTAT value. Furthermore, the date format should be amended from the American style to the British standard. Finally, participants emphasised the need to clearly differentiate between *aTAT* and the *Analytical phase* presented in the dashboard through more precise labelling, as these refer to two different parameters. It was also recommended to revise *TAT* and *aTAT* references to ensure consistency throughout the dashboard.

5.3 Changes after Usability Study

The reset filters button was difficult to find for most of the participants, who did not recognise the symbol used. The symbol was changed to another icon that may be more recognised as reset/undo, and the icon was surrounded by a border with a shadow to further emphasise that this is a button that can be clicked.

Following the feedback from users, a search function was added to the test name filter to make it easier to search for a particular test, as the option list is quite exhaustive.

Although the dashboard was designed to be as minimal as possible to avoid an overload of information in keeping with best practice guidelines (See Section 2.4.3 Key considerations in dashboard design), the usability study uncovered the need to have more labelling for a clearer indication of the different metrics being displayed. All visualisation labels were revised to ensure clarity and legibility across all the labelling text. The definition of aTAT, which was a metric used throughout the dashboard, was included as a footnote to ensure clarity of the measures for the user.

The tree-map visualisation showing the different testing phases was changed to a stacked bar chart with labels for each phase outside of the bar chart. This enabled a clearer display of the phase labels and also allowed a setup showing the phases in their chronological order. This was achieved by creating another table with the sort order for the different phases, and using this sort order to sort the phases in the bar chart. The table displaying the highest TAT values were revised to show the Sample ID first followed by the TAT, as preferred by the users. The final dashboard design can be seen in Figure 13.

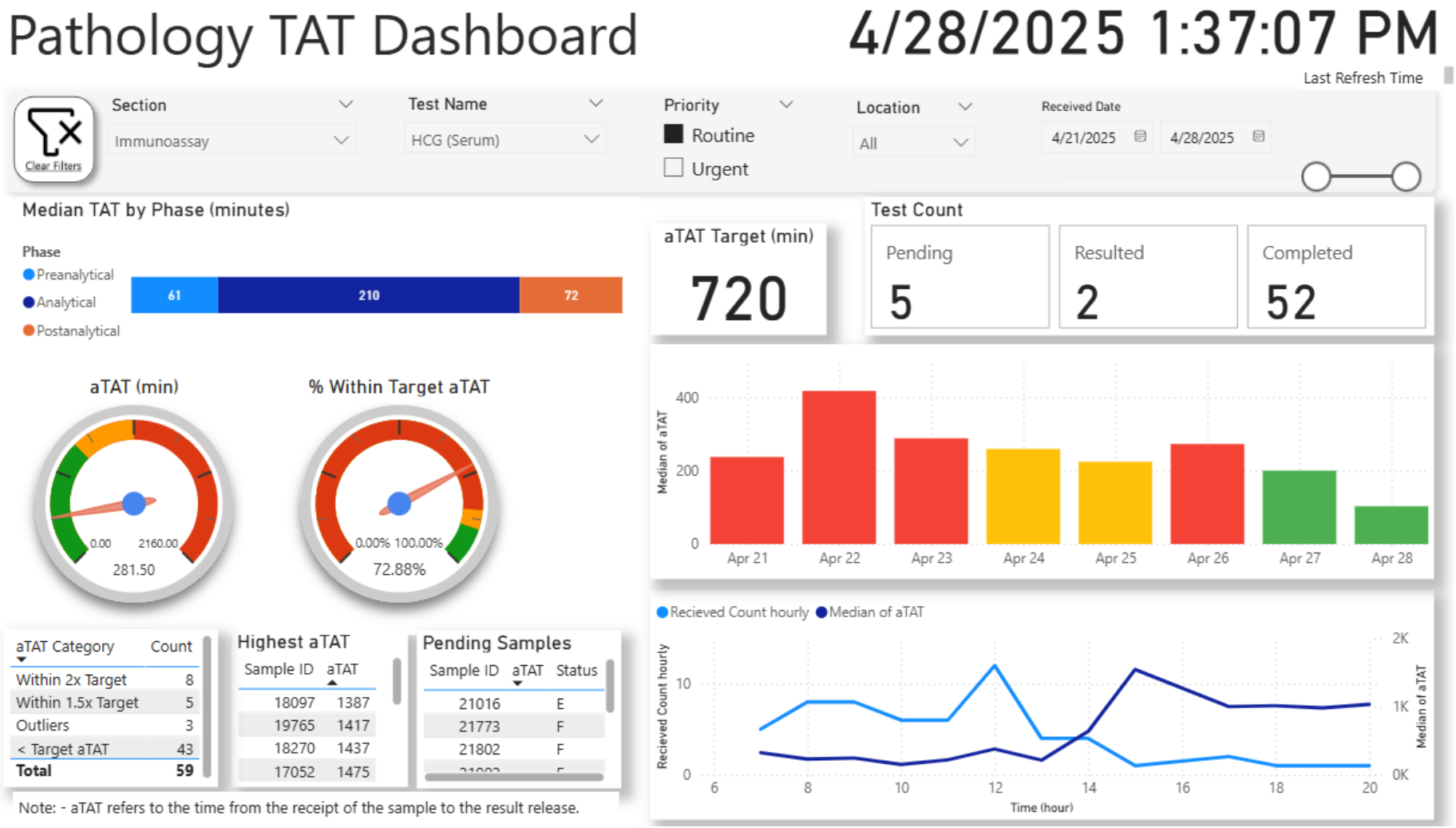


Figure 13 Final (Third) Dashboard Design

6 Limitations

6.1 Participant Selection

Due to the limited number of staff involved in quality management, the participants in the usability study were from the same laboratory manager pool, who took part in the requirements gathering stage. While their prior involvement enabled them to give feedback closely aligned with the dashboard's intended objectives, it also introduced potential positive bias. Familiarity with the system's functions and design discussions may have made navigation and task completion easier than it would be for first-time users, potentially affecting usability scores.

Future usability testing could therefore benefit from including a broader range of participants—such as end users with no prior exposure to the system—to validate findings under conditions closer to first-time, unassisted use.

6.2 Test-level data

This study evaluated TAT data exclusively at the test level, meaning each laboratory test result was treated as a separate unit of analysis. While this approach provides valuable insight into turnaround performance for specific assays, it does not account for the fact that a single patient sample can contain multiple tests within the same order. Analysing data at the sample level could reveal additional operational patterns—such as delays affecting multiple tests on the same specimen—or identify workflow bottlenecks linked to specimen handling rather than to individual assays. Incorporating both test-level and sample-level perspectives in future analyses would enable a more comprehensive understanding of TAT performance and its underlying causes.

6.3 Retrospective data extracts

Due to institutional IT restrictions, this study relied on retrospective data extracts provided in CSV format. Although this data could be updated at periodic intervals, this approach does not allow full integration with live LIS data streams. Therefore, real-time performance in a live environment could

not be demonstrated and issues such as latency, system load and network reliability could not be assessed.

6.4 Limited Scope

The dashboard was designed exclusively for blood tests and applications to other disciplines of laboratory practice, such as histopathology, may have different requirements. The generalisability of the solution to these disciplines remains untested.

Also, the context of a single institution (Mater Dei Hospital) limits the applicability of the solution to other environments, without additional adaptations.

7 Future Work

This thesis has demonstrated the use of a TAT dashboard as an effective and usable tool in monitoring turnaround times. However, there are several opportunities to expand the scope of this solution to expand its functionality and further validate its impact.

7.1 Broader Scope of Dashboard

The dashboard could be enhanced to include additional laboratory performance indicators, such as specimen rejection rates or repeat testing frequency. These additional KPIs would provide a more comprehensive operational view. Future iterations could also extend analysis beyond the test level to the sample level. This would enable identification of cases where multiple tests on the same order are delayed, offering a more holistic understanding of workflow bottlenecks and their impact on patient care.

The adaptability of the dashboard for other laboratory disciplines and other institutions can also be explored. The same underlying principles of continuous monitoring, visualisation, and real-time alerting can be extended to other areas of healthcare practice. For example, similar dashboards could be implemented in emergency departments to monitor patient throughput, from admission to discharge, or in imaging and surgical services to track turnaround times for diagnostic reporting and procedure scheduling.

This would enable the identification of bottlenecks, improve responsiveness, and enhance overall efficiency. This highlights the broader potential of dashboard-based approaches as versatile tools for healthcare quality improvement beyond the laboratory context.

7.2 Broader Usability Testing

The dashboard usability testing can be extended to a wider range of end-users, including those with no prior exposure to the dashboard or involvement in quality management. This would validate findings under conditions closer to first-time, unassisted use.

7.3 Artificial Intelligence and Predictive Analysis

Artificial Intelligence (AI), and specifically Machine Learning (ML) could be integrated into the dashboard to provide predictive insights. Potential TAT breaches can be forecast before they occur, providing an opportunity for proactive interventions [35]. Similarly, anomaly detection algorithms could identify unusual delays or abnormal trends automatically, allowing earlier investigation and resolution.

AI could also forecast test request arrivals, recommending staffing adjustments or analyser allocations for upcoming shifts. This can be done by integrating staff allocation and analyser allocation data. AI can also let users test different scenarios and workflow changes and how these can affect TAT.

8 Conclusions

This research set out to develop and assess a dashboard designed to monitor laboratory turnaround times for blood tests at a local hospital laboratory. The work was motivated by the shortcomings of current methods, where reporting methods are static, retrospective and riddled with inefficient methods that limit opportunities for timely action.

With the adoption of dashboard design principles, this project demonstrated how real-time monitoring and data visualisation can provide laboratory managers with actionable insights to improve efficiency and quality. Using Microsoft Power BI, data extracted from the LIS were transformed into performance indicators, including median TAT, compliance with target thresholds, and phase-specific metrics. Usability testing with laboratory managers showed that the tool was easy to use and presented relevant metrics in a clear, accessible format.

These findings emphasise the value of dashboards as operational tools in laboratory quality management, bridging the gap between raw LIS data and meaningful action.

The principles underlying this dashboard solution extend beyond the laboratory setting. Similar dashboards can be used in an emergency setting to track patient flow, to monitor the reporting process in imaging or to monitor other quality initiatives in broader hospital settings. Future work can therefore explore the use of these dashboards in other settings as well as their clinical impact.

In conclusion, this project demonstrated that interactive dashboards, based on user-centred design and sound data governance, can reshape how turnaround times are tracked and managed, resulting in more responsive operations and ultimately improved patient care.

Works Cited

[1] B. E. Vrijsen, S. Haitjema, J. Westerink, C. A. Hulsbergen-Veelken, W. W. van Solinge and M. J. ten Berg, "Shorter laboratory turnaround time is associated with shorter emergency department length of stay: a retrospective cohort study," *BMC Emergency Medicine,* no. 207, 2022.

[2] L. L. Holland, L. L. Smith and K. E. Blick, "Reducing laboratory turnaround time outliers can reduce emergency department patient length of stay: and 11-hospital study," *American Journal of Clinical Pathology,* vol. 124, no. 5, pp. 672-4, 2005.

[3] N. Cassim, M. E. Tepper, L. M. Coetzee and D. K. Glencross, "Timely delivery of laboratory efficiency information, Part I: Developing an interactive turnaround time dashboard at a high-volume laboratory.," *African Journal of Laboratory Medicine,* vol. 9, no. 2, 2020.

[4] Mater Dei Laboratory Information System, "Internal Dataset," Msida, 2025.

[5] F. Halwani, W. C. Li, D. Banerjee, L. Lessard, D. Amyot, W. Michalowski and R. Giffen, "A real-time dashboard for managing pathology processes," *Journal of Pathology Informatics,* vol. 4, no. 7, p. 24, 2016.

[6] N. Cassim, L. M. Coetzee, M. E. Tepper, L. Perelson and D. K. Glencross, "Timely delivery of laboratory efficiency information, Part II: Assessing the impact of a turn-around time dashboard at a high-volume laboratory," *African Journal of Laboratory Medicine,* vol. 9, no. 2, p. 948, 2020.

[7] V. Bartolo, "The Impact of Laboratory Information Systems on the Efficient Management of Laboratories," University of Malta, Msida, 2009.

[8] G. D. Lundberg, "Acting on significant laboratory results," *JAMA,* vol. 245, no. 17, pp. 1762-1763, 1981.

[9] M. Plebani, M. Laposata and G. D. Lundberg, “The Brain-to-Brain Loop Concept for Laboratory Testing 40 Years After Its Introduction,” *Am J Clin Pathol,* vol. 136, pp. 829-833, 2011.

[10] E. Piva, M. Pelloso, L. Penello and M. Plebani, “Laboratory critical values: Automated notification supports effective clinical decision making,” *Elsevier Clinical Biochemistry,* vol. 47, no. 13-14, pp. 1163-1168, 2014.

[11] J. T. Barr and S. Silver, “The total testing process and its implications for laboratory administration and education,” *Clin Lab Manager Rev,* vol. 8, no. 5, pp. 526-542, 1994.

[12] A. Debono, “Managing Information in the Hospital's Pathology Department,” University of Malta, Msida, 2008.

[13] I. M. Lubin, R. Astles, J. D. Bunn, N. E. Cornish, G. Lazaro, A. A. Marshall, H. L. Stang and V. R. De Jesus, “The Clinical Laboratory is an Integral Component to HEalth Care Delivery; An Expanded Representation of the Total Testing PRocess,” *American Journal of Clinical Pathology,* vol. 160, pp. 124-129, 2023.

[14] P. Valenstein, “Laboratory Turnaround Time,” *American Journal of Clinical Pathology,* vol. 105, no. 6, 1996.

[15] N. Sarin and S. K. Yadav, “Role of Information Technology,” in *Clinical Laboratory Management*, Cham, Switzerland, Springer, 2023, pp. 187-192.

[16] D. Parmenter, Key Performance Indicators, USA: John Wiley & Sons, 2015.

[17] I. Setiawan and H. H. Purba, “A Systematic Literature Review of Key Performance Indicators (KPIs) Implementation,” *Journal of Industrial Engineering and Management Research,* vol. 1, no. 3, pp. 200-208, 2020.

[18] S. Singh and R. Gupta, “Benchmarking and Key Performance Indicators,” in *Clinical Laboratory Management*, Cham, Switzerland, Springer, 2023, pp. 169-174.

[19] G. Speziale, “Strategic Management of a Healthcare Organization: Engagement, Behavioural Indicators, and Clinical Performance,” *European Heart Journal Supplements,* vol. 17, pp. A3-A7, 2015.

[20] R. Rabiei, Y. M. Moghadam, N. Aslani, A. Garavand, A. Kazennejad and S. Abhari, “Knowledge management status in a non-governmental public hospital: the current status and improvement solutions,” *Journal of Health Management and Informatics,* vol. 7, no. 1, pp. 24-30, 2020.

[21] S. C. Buttigieg, A. Pace and C. Rathert, “Hospital performance dashboards: a literature review,” *Journal of Health Organization and Management,* 2017.

[22] B. A. Wilbanks and P. A. Langford, “A Review of Dashboards for Data Analytics in Nursing,” *CIN: Computers, Informatics, Nursing,* vol. 32, no. 11, pp. 545-549, 2014.

[23] N. Azzopardi-Muscat, S. Buttigieg, N. Calleja and S. Merkur, “Health Systems in Transition,” 2017. [Online]. Available: https://platform.who.int/docs/default-source/mca-documents/policy-documents/report/MLT-CC-37-01-REPORT-2017-eng-Malta-Hit-report.pdf. [Accessed 1 October 2025].

[24] R. C. Hawkins, “Laboratory Turnaround Time,” *The Clinical Biochemist Reviews,* vol. 28, no. 4, pp. 179-194, 2007.

[25] N. Cherie, D. M. Berta, M. Tamir, Z. Yiheyis, A. A. Angelo, A. M. Tarekegn, E. Chane, M. Nigus and B. B. Teketelew, “Improving laboratory turnaround times in clinical settings: A systematic review of the impact of lean methodology application,” *PLOS One,* vol. 19, no. 10, 2024.

[26] B. Sen, B. Arslan, T. S. D. Bulut, B. Narli, N. Afandiyeva, G. Koca, C. Yilmaz and O. Gulbahar, “Improvement of the post-analytical phase by

means of an algorithm based autoverification," *De Gruyter,* vol. 48, no. 6, pp. 626-33, 2023.

[27] A. L. Leber, E. Peterson and J. D. Bard, "The Hidden Crisis in the Times of COVID-19: Critical Shortages of Medical Laboratory Professionals in Clinical Microbiology," *Journal of Clinical Microbiology,* vol. 60, no. 8, pp. 241-22, 2022.

[28] A. K. Petrides, I. Bixho, E. M. Goonan, D. W. Bates, S. Shaykevich, S. R. Lipsitz, A. B. Landman, M. J. Tanasijevic and S. E. Melanson, "The Benefits and Challenges of an Interfaced Electronic Health Record and Laboratory Information System: Effects on Laboratory Processes," *Archives of Pathology & Laboratory Medicine,* vol. 141, no. 3, pp. 410-7, 2017.

[29] International Organization for Standardization, "ISO 15189:2022. Medical Laboratories - Requirement for quality and competence," December 2022. [Online]. Available: https://www.iso.org/standard/76677.html. [Accessed 1 May 2025].

[30] C. lalongo, O. Porzio, I. Giambini and S. Bernardini, "Total Automation for the Core Laboratory: Improving the Turnaround Time Helps to Reduce the Volume of Ordered STAT Tests," *Journal of Laboratory Automation,* vol. 21, no. 3, pp. 451-8, 2016.

[31] P. P. Dawande, R. S. Wankhade, F. I. Akhtar and O. Noman, "Turnaround Time: An Efficacy Measure for Medical Laboratories," *Cureus,* vol. 14, no. 9, 2022.

[32] W. Huf, M. Mohns, T. Garmatiuk, R. Lister, C. Buchta, B. Ettl and U. Koller, "Benchmarking diagnostic laboratory performance: Survey results for Germany, Austria, and Switzerland," *Springer Nature,* vol. 134, no. 3, pp. 174-181, 2021.

[33] S. Few, Information Dashboard Design - The Effective Visual Communication of Data, California: O'Reilly Media, 2006.

[34] S. Ghosh, R. Aggarwal, R. S. Mavuduru, G. S. Bora, V. Kumar and A. Suri, "Development of a business intelligence dashboard for real-time monitoring of clinical quality indicators," *BMJ Health & Care Informatics,* vol. 27, no. 3, 2020.

[35] E. R. Tsai, D. Demirtas, N. Hoogendijk, A. N. Tintu and R. J. Boucherie, "Turnaround time prediction for clinical chemistry samples using machine learning," *De Gruyter Brill,* vol. 60, no. 12, 2022.

[36] M. Eminogaoglu and A. Vahaplar, "Turnaround Time Prediction for a Medical Laboratory Using Artificial Neural Networks," *Journal of Information Technologies,* vol. 11, no. 4, pp. 357-368, 2018.

[37] P. N. Valenstein and K. Emancipator, "Sensitivity, Specificity, and Reproducibility of Four Measures of Laboratory Turnaround Time," *American Journal of Clinical Pathology,* vol. 91, no. 4, pp. 453-457, 1989.

[38] M. Plebani, L. Sciacovelli and A. Aita, "Quality Indicators for the Total Testing Process," *Clinics in Laboratory Medicine,* vol. 37, no. 1, pp. 187-205, 2017.

[39] S. J. Steindel and D. A. Novis, "Using Outlier Events to Monitor Test Turnaround Time: A College of American Pathologists Q-Probes Study in 496 Laboratories," *Archives of Pathology Laboratory Medicine,* vol. 123, no. 7, pp. 607-614, 1999.

[40] R. T. Vollmer, "Analysis of Turnaround Times in Pathology: an approach using failure time analysis," *Americna Journal of Clnical Pathology,* vol. 126, no. 2, pp. 215-20, 2006.

[41] M. K. Goel, P. Khann and J. Kishore, "Understanding survival analysis: Kaplan-Meier estimate," *International Journal of Ayurveda Research,* vol. 1, no. 4, pp. 274-8, 2010.

[42] B. A. Jones, M. K. Walsh and S. G. Ruby, "Hospital nursing satisfaction with clinical laboratory services: a College of American Pathologists Q-

Probes study of 162 institutions.," *Archives of Pathology and Laboratory Medicine,* vol. 130, no. 12, pp. 1756-61, 2006.

[43] L. H. Hilborne, R. K. Oye, J. E. McArdle, J. A. Repinski and D. O. Rodgerson, "Evaluation of Stat and Routine Turnaround Times as a Component of Laboratory Quality," *American Journal of Clinical Pathology,* vol. 91, no. 3, pp. 331-5, 1989.

[44] H. P. Pati and G. Singh, "Turnaround Time (TAT): Difference in Concept for Laboratory and Clinician," *Indian Journal of Hematology and Bood Transfusion,* vol. 30, no. 2, pp. 81-84, 2012.

[45] M. Plebani, "Errors in clinical laboratories or errors in laboratory medicine?," *Clinical Chemistry and Laboratory Medicine,* vol. 44, no. 6, pp. 750-9, 2006.

[46] L. Sciacovelli, M. O'Kane, Y. Abdelwahab Skaik, P. Caciagli, C. Pellegrini, G. Da Rin, A. Ivanov, T. Ghys, M. Plebani and IFCC WG-LEPS, "Quality Indicators in Laboratory Medicine: from theory to practice. Preliminary data from the IFCC Working Group Project "Laboratory Errors and Patient Safety"," *Clinical Chemistry and Laboratory Medicine,* vol. 49, no. 5, pp. 835-44, 2011.

[47] J. A. Linder, J. L. Schnipper, R. Tsurikova, D. T. Yu, L. A. Volk, A. J. Melnikas, M. B. Palchuk, M. Olsha-Yehiav and B. Middleton, "Electronic health record feedback to improve antibiotic prescribing for acute respiratory infections," *American Journal of Managed Care,* vol. 12, pp. 311-9, 2010.

[48] J. Theuma, "Enhancing an existing patient dashboard with the use of Internet of Things," University of Malta, Msida, 2020.

[49] K. Pauwels, T. Ambler and T. Wiesel, "Dashboards as a Service: Why, What, How, and What Research Is Needed?," *Journal of Service Research,* vol. 12, no. 2, 2009.

[50] E. Kroch, T. Vaughn, M. Koepke, S. Roman, D. Foster, S. Sinha and S. Levey, “Hospital boards and quality dashboards,” *Journal of Patient Safety,* 2006.

[51] R. Person, Balanced Scorecards and Operational Dashboards with Microsoft Excel, Indianopolis: John Wiley & Sons Inc, 2013.

[52] A. Pace and S. C. Buttigieg, “Can hospital dashboards provide visibility of information from bedside to board? A case study approach,” *Emerald Insight,* vol. 2, p. 31, 2017.

[53] J. Weiner, V. Balijepally and M. Tanniru, “Integrating Strategic and Operational Decision Making Using Data-Driven Dashboards: The Case of St. Joseph Mercy Oakland Hospital,” *Journal of Healthcare Management,* vol. 60, no. 5, pp. 319-330, 2015.

[54] D. Dowding, R. Randell, P. Gardner, G. Fitzpatrick, P. Dykes, J. Favela, S. Hamer, Z. Whitewood-Moores, N. Hardiker, E. Borycki and L. Currie, “Dashboards for improving patient care: a review of the literature,” *International Journal of Medical Informatics,* vol. 84, no. 2, pp. 87-100, 2015.

[55] R. Rabiei and S. Almasi, “Requirements and challenges of hospital dashboards: a systematic literature review,” *BMC Medical Informatics and Decision Making,* vol. 22, no. 287, 2022.

[56] S. S. Jones, R. S. Rudin, T. Perry and P. G. Shekelle, “Health Information Technology: an updated systematice review with a focus on meaningful use,” *Annals of Internal Medicine,* vol. 160, no. 1, pp. 48-54, 2014.

[57] R. Rabiei and S. Almasi, “Requirements and challenges of hospital dashboards: a systematic literature review,” *BMC Meidcal Informatics and Decision Making,* vol. 22, no. 287, 2022.

[58] J. Nielsen, “10 Usability Heuristics for User Interface Design,” Nielsen Norman Group, 30 January 2024. [Online]. Available:

https://www.nngroup.com/articles/ten-usability-heuristics/. [Accessed 5 April 2025].

[59] Microsoft, “Tips for designing a great Power BI dashboard,” 30 June 2023. [Online]. Available: https://learn.microsoft.com/en-us/power-bi/create-reports/service-dashboards-design-tips. [Accessed 15 May 2025].

[60] Syntrix Consulting Group, “10 Best Practices in Healthcare Dashboard Design,” 2024. [Online]. Available: https://www.syntrixconsulting.com/blog/10-best-practices-in-healthcare-dashboards-design. [Accessed 5 April 2025].

[61] “UX/UI Best Practices for Healthcare Analytics Dashboards,” Side Kick, 2025. [Online]. Available: https://www.sidekickinteractive.com/designing-your-app/uxui-best-practices-for-healthcare-analytics-dashboards/. [Accessed 5 April 2025].

[62] M. Caposino, “Healthcare Dashboard Design Best Practices and Key Considerations,” fuselab creative, 2022. [Online]. Available: https://fuselabcreative.com/healthcare-dashboard-design-best-practices/. [Accessed 5 April 2025].

[63] J. Underwood and J. Fox, “Microsoft Power BI Updates Blog - The Art and Science of Effective Dashboard Design,” Microsoft, 29 September 2015. [Online]. Available: https://powerbi.microsoft.com/en-us/blog/the-art-and-science-of-effective-dashboard-design/. [Accessed 15 May 2025].

[64] P. Laubheimer, “Dashboards: Making Charts and Graphs Easier to Understand,” 18 June 2017. [Online]. Available: https://www.nngroup.com/articles/dashboards-preattentive/. [Accessed 5 April 2025].

[65] HSE, “Dashboards & Data Visualisation in Healthcare,” March 2025. [Online]. Available: https://www.hse.ie/eng/services/list/5/publichealth/publichealthdepts/i

mprhealthservice/1-0-healthcare-dashboards-and-data-visualisation-learning-report-march-2025v01.pdf. [Accessed 1 May 2025].

[66] K. Wairimu, "The Role of Data Visualization in Enhancing Patient Health Literacy," *Research Invention Journal of Biological and Applied Sciences,* vol. 4, no. 1, pp. 36-40, 2024.

[67] Microsoft, "Create Key Performance Indicator (KPI) visualizations," 29 November 2023. [Online]. Available: https://learn.microsoft.com/en-us/power-bi/visuals/power-bi-visualization-kpi?tabs=powerbi-desktop. [Accessed 1 May 2025].

[68] F. van de Baan, S. Lambregts, E. Bergman, J. Most and D. Westra, "Involving Health Professionals in the Development of Quality and Safety Dashboards: Qualitative Study," *JMIR Publications Advancing Digital Health & Open Science,* vol. 25, 2023.

[69] H. J. Evan lten, S. Sulz, E. M. van Raaij and R. Wehrens, "Big Data Health Care Innovations: Performace DAhsboarding as a Process of Collective Semsemaking," *Journal of Medical Internet Research,* vol. 24, no. 2, 2022.

[70] F. S. Rossi, M. C. Adams, G. Aarons and M. P. McGovern, "From glitter to gold: recommendations for effective dashboards from design through sustainment," *Implementation Science,* vol. 20, no. 16, 2025.

[71] Roche, "navify Analytics for Core Lab," F.Hoffmann-La Roche Ltd, [Online]. Available: https://navify.roche.com/marketplace/products/navify-analytics-for-core-lab#explore-more. [Accessed 15 June 2025].

[72] Roche, "navify Lab Operations," Roche Diagnostics Ltd, 2025. [Online]. Available: https://diagnostics.roche.com/gb/en/products/instruments/cobas-infinity-laboratory-solution.html?utm_source=chatgpt.com. [Accessed 15 June 2025].

[73] E. Maury, M.-O. Boldi, G. Greub, V. Chavez, K. Jaton and O. Opota, “An Automated Dashboard to Improve Laboratory COVID-19 Diagnostics Management,” *Frontiers in Digital Health,* vol. 3, 2021.

[74] M. H. Rivero, “An open-source application built with R programming language for clinical laboratories to innovate process of excellence and overcome the uncertain outlook during the global healthcare crisis,” in *International Conference on Computational Science and Computational Intelligence (CSCI)*, 2020.

[75] M. B. Morgan, B. F. Branstetter IV, D. M. Lionetti, J. s. Richardson and P. J. Chang, “The Radiology Digital Dashboard: Effects on Report Turnaround Time,” *Journal of Digital Imaging,* vol. 21, no. 1, pp. 50-58, 2007.

[76] A. H. Dhanaliwala, A. J. Deutsch, J. Moon, D. Lalevic, C. Chambers and T. S. Cook, “Development and Deployment of an Emergency Department Radiology Dashboard to Improve Communication and Transparency of Radiologic Imaging and Report Status,” *Journal of the American College of Radiology,* vol. 22, no. 2, pp. 191-199, 2025.

[77] “Figma,” Figma, [Online]. Available: https://www.figma.com.

[78] Salesforce, “Tableau from Salesforce,” 2025. [Online]. Available: https://www.tableau.com/. [Accessed 15 June 2025].

[79] Plotly, “Plotly,” 2025. [Online]. Available: https://plotly.com/dash/. [Accessed 15 June 2025].

[80] Microsoft, “Power BI Documentation,” Microsoft Learn, 2024. [Online]. Available: https://learn.microsoft.com/en-us/power-bi/. [Accessed 1 May 2025].

[81] 3Cloud, “Leveraging Power BI for Large Datasets,” 16 July 2024. [Online]. Available: https://3cloudsolutions.com/resources/leveraging-power-bi-for-large-datasets/. [Accessed 1 May 2025].

[82] Microsoft, “Data reduction techniques for Import modeling,” 30 December 2024. [Online]. Available: https://learn.microsoft.com/en-us/power-bi/guidance/import-modeling-data-reduction. [Accessed 1 May 2025].

[83] SQLBI, “The DAX language,” 1 June 2025. [Online]. Available: https://dax.guide/.

[84] Microsoft, “Data Analysis Expressions (DAX) Reference,” Microsoft, 2025. [Online]. Available: https://learn.microsoft.com/en-us/dax/. [Accessed 1 May 2025].

[85] WHO Regional Office for Europe, “Tools for making good data visualizations: the art of charting,” 2021. [Online]. Available: https://iris.who.int/handle/10665/342568. [Accessed 1 May 2025].

[86] Salesforce, “Tableau Desktop and Web Authoring Help - Best Practices for Effective Dashboards,” Tableau, 2025. [Online]. Available: https://help.tableau.com/current/pro/desktop/en-us/dashboards_best_practices.htm. [Accessed 1 May 2025].

[87] K. Pernice, “F-Shaped Pattern of Reading on the Web: Misunderstood, But Still Relevant (Even on Mobile),” Nielsen Norman Group, 12 November 2017. [Online]. Available: https://www.nngroup.com/articles/f-shaped-pattern-reading-web-content/?utm_source=chatgpt.com. [Accessed 1 June 2025].

[88] M. Alhamadi, H. Alsayahani, S. Clinch and M. Vigo, “Behavioural Indicators of Usability in Visual Analytics Dashboards,” *ACM Transactions on Interactive Intelligent Systems,* vol. 15, no. 2, pp. 1-35, 2025.

[89] K. Nunes, A. Passos, M. Menezes, F. Feyh, C. Moura, L. Pinheiro, A. Santos, A. Silva, J. Dallyson, I. Francyles and L. Rivero, “Applying Checklist and Design Patterns for Evaluating and Redesigning a Dashboard Interface of a Decision Support Information System,” in

Proceedings of the 27th International Conference on Enterprise Information Systems, Brazil, 2025.

[90] A. Madan and S. K. Dubey, "Usability Evaluation Methods: A Literature Review," *International Journal of Engineering Science and Technology (IJEST),* vol. 4, no. 2, pp. 590-599, 2012.

[91] J. Nielsen and T. Landauer, "A Mathematical Model of the Finding of Usability Problems," in *CHI '93: Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems*, Amsterdam, The Netherlands, 1993.

[92] J. Nielsen, "Why You Only Need to Test with 5 Users," Nielsen Norman Group, 18 March 2000. [Online]. Available: https://www.nngroup.com/articles/why-you-only-need-to-test-with-5-users/. [Accessed 15 June 2025].

[93] J. Brooke, "SUS: A quick and dirty usability scale," *Usability Eval Ind,* vol. 11, no. 30, 1995.

[94] A. Bangor, P. Kortum and J. Miller, "Determining What Individual SUS Scores Mean: Adding an Adjective Rating Scale," *Journal of Usability Studies,* vol. 4, no. 3, pp. 114-123, 2009.

[95] B. Al Qassabai, R. AlSukaiti, S. Alajmi, A. S. Omar, R. Ibrahin, A. A. Banibakr, K. Al-Baimani, A. Zribi, S. N. AlDhali, M. Majed, M. M. AlGhaiti, a. Q. AlBalushi, N. S. Alhasni, S. Al Sheedi, H. S. Al-Awaisi, N. Al-Riyami and O. Ayaad, "Improving Turnaround Times and Operational Efficiency in Radiology Services: Quality Improvement Study in Oman," *Asian Pacific Journal of Cancer Prevention,* vol. 26, no. 5, pp. 1709-18, 2025.

Appendix A: Participant Information Letter

L-Università ta' Malta

Information Letter

30th October 2024

Dear Participant

My name is Sephora Camilleri and I am a student at the University of Malta, presently reading for a MSc in Digital Health. I am conducting a research study for my dissertation titled 'Development of Turnaround Time Dashboard for Hospital Blood Tests'; this is being supervised by Dr Conrad Attard. This letter is an invitation to participate in this study. Below you will find information about the study and about what your involvement would entail, should you decide to take part.

My study aims to develop a real-time, interactive Turnaround Time (TAT) dashboard that allows the dynamic monitoring of turnaround times. By automating data extraction and visualization, it will enable faster identification of delays, improve workflow efficiency, and provide insights that enhance patient care. Your participation in this study would help contribute to a better understanding of how this type of solution can impact laboratory management practices. Any data collected from this research will be used solely for purposes of this study.

Should you choose to participate, you will be asked to participate in an interview discussing your experiences, opinions, and suggestions related to the proposed design and features of the solution. This would be followed up by another session where the designed solution is tested for its usability. The testing phase will involve using the application to simulate real-world scenarios and providing feedback on its performance. Both sessions will take approximately 30 minutes to complete.

Data collected will be anonymised and stored on one password-protected personal computer. Any material in hard copy form will be placed in a locked cupboard. Only my supervisor and myself (and in exceptional cases, examiners) will have access to this data. If you want to enquire who accessed your personal data, please contact myself, Sephora Camilleri or my supervisor, Dr Conrad Attard using contact details at the end of this letter.

The findings which emerge from this research may be published (e.g., in a dissertation, academic journals) and/or presented (e.g., during conferences, meetings). Your name (or any other identifying information) will not appear when the findings are reported.

Participation in this study is entirely voluntary; in other words, you are free to accept or refuse to participate, without needing to give a reason. You are also free to withdraw from the study at any time, without needing to provide any explanation and without any negative repercussions for you. Should you choose to withdraw, any data collected from your interview will be erased as long as this is technically possible (for example, before it is anonymised or published), unless erasure of data would render impossible or seriously impair achievement of the research objectives, in which case it shall be retained in an anonymised form.

If you choose to participate, please note that there are no direct benefits to you. This research may benefit others by providing a solution to monitor turnaround times (TATs), supporting data-driven decision-making, and improving patient outcomes through faster diagnostic reporting and improved quality of care. Your participation does not entail any known or anticipated risks.

Please note also that, as a participant, you have the right under the General Data Protection Regulation (GDPR) and national legislation to access, rectify and where applicable ask for the data concerning you to be erased.

All data collected will be erased on completion of the study and following publication of results within 1 year of completion of the study.

A copy of this information sheet is being provided for you to keep and for future reference.

Thank you for your time and consideration. Should you have any questions or concerns, you may contact myself or my supervisor on the details provided below.

Yours Sincerely,

_____	_____
Sephora Camilleri	**Dr Conrad Attard**
sephora.camilleri.09@um.edu.mt	**conrad.attard@um.edu.mt**

Appendix B: Participant Consent Form

L-Università ta' Malta

Participant's Consent Form

Development of a Turnaround Time Dashboard for Hospital Blood Tests

I, the undersigned, give my consent to take part in the study conducted by Sephora Camilleri**.** This consent form specifies the terms of my participation in this research study.

1. I have been given written and/or verbal information about the purpose of the study; I have had the opportunity to ask questions and any questions that I had were answered fully and to my satisfaction.
2. I also understand that I am free to accept to participate, or to refuse or stop participation at any time without giving any reason and without any penalty. Should I choose to participate, I may choose to decline to answer any questions asked. In the event that I choose to withdraw from the study, any data collected from me will be erased as long as this is technically possible (for example, before it is anonymised or published), unless erasure of data would render impossible or seriously impair achievement of the research objectives, in which case it shall be retained in an anonymised form.
3. I understand that I have been invited to participate in an interview followed by a usability test in which the researcher will interview me to analyse how the proposed solution would be of benefit to laboratory management practices. A follow up usability test will be carried out by the researcher to test the usability of the designed solution. I am aware that both the interview and the follow up usability testing will take approximately 30 minutes. I understand that the interview and the usability testing will be conducted in a place and at a time that is convenient for me.
4. I understand that my participation does not entail any known or anticipated risks.
5. I understand that there are no direct benefits to me from participating in this study. I also understand that this research may benefit others by providing a solution to monitor turnaround times (TATs), supporting data-driven decision-making, and improving patient outcomes through faster diagnostic reporting and improved quality of care.

6. I understand that, under the General Data Protection Regulation (GDPR) and national legislation, I have the right to access, rectify, and where applicable, ask for the data concerning me to be erased.
7. I understand that all data collected will be erased on completion of the study and following publication of results within 1 year of completion of the study.
8. I am aware that my identity and personal information will not be revealed in any publications, reports or presentations arising from this research.
9. I have been provided with a copy of the information letter and understand that I will also be given a copy of this consent form.
10. I am aware that extracts from my interview may be published (e.g., in a dissertation, academic journals) and/or presented (e.g., during conferences, meetings), either in anonymous form, or using a pseudonym (a made-up name or code, e.g., respondent A).
11. I am aware that, by marking the first tick-box below, I am giving my consent for the identity of the organisation I represent to be revealed in publications (e.g., in a dissertation, academic journals), reports or presentations (e.g., during conferences, meetings), arising from this research, and responses I provide may be quoted directly or indirectly.

MARK ONLY IF AND AS APPLICABLE

- ☐ I agree that the identity of the organisation I represent may be disclosed in publications/presentations.
- ☐ I do not agree that the identity of the organisation I represent may be disclosed in publications/presentations.

I have read and understood the above statements and agree to participate in this study.

Name of participant:_____

Signature:_____

Date: _____

Sephora Camilleri **Dr Conrad Attard**

sephora.camilleri.09@um.edu.mt **conrad.attard@um.edu.mt**

Appendix C: Interview Guide

1. Introduction of Project: Brief the interviewee on the purpose of the interview and the project.

2. Background Information: Interviewee's role and their interaction with laboratory data.

1. Can you describe your role and daily responsibilities in the laboratory/clinical setting?
2. How often do you interact with laboratory data, particularly regarding turnaround times for test results?
3. How do you currently monitor and manage the TAT for blood tests? What tools or systems do you currently use?

3. Current TAT Monitoring Challenges

1. What are the limitations or pain points of the current TAT tracking system?
2. Can you share an example of when a delay in TAT impacted patient care or laboratory efficiency?
3. How quickly do you need access to TAT data to take corrective action?

4. Expectations for the Dashboard

1. What specific metrics or information would you like to see on a real-time TAT dashboard?
2. How would you prefer to filter or view data (e.g., by test type, priority, time range)?
3. What types of visualizations (e.g., charts, graphs) would be most useful for monitoring TAT?

4. Would real-time alerts for delays be helpful? If so, how would you like to receive these alerts?
5. How would this dashboard improve your day-to-day operations compared to the current system?

5. Usability and Design Preferences

1. What would make the dashboard easy to use in your workflow? (e.g., simplicity, speed, mobile access)
2. How often would you anticipate using the dashboard?
3. Would you prefer a customizable interface, where you can adjust views and data displays based on your needs?
4. What kind of training or support would you need to use this dashboard effectively?

6. Prototyping Feedback

1. Based on this prototype, what features stand out as particularly useful for your needs?
2. Is there anything missing that you would like to see included?
3. Are there any areas where the design could be more intuitive or efficient for your use?

7. Additional remarks

1. Is there anything else you'd like to share that could help make the dashboard more effective for you and your team?
2. What would success look like for you in terms of this TAT dashboard's impact on your work?

Appendix D: Usability Study Sheet

Instructions for Usability Study TAT Dashboard

You will be given access to the TAT dashboard workspace. Please attempt the following tasks on the dashboard and write your answers in the space provided.

Task 1: Identify the latest data refresh time

- Answer _____
- Was the information easy to find? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Task 2: What is the aTAT for Troponin T for 28th April 2025?

- Answer _____
- Was the information easy to find? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Task 3: Reset all filters.

- Was the function easy to find? [Yes / No]

Task 4: What is the percentage of samples within Target aTAT for Urgent Calcium between 1st and 18th April 2025

- Answer _____
- Was the information easy to find? [Yes / No]
- Was the percentage of samples within target easy to understand? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Task 5: Which is the sample with the highest aTAT for Albumin (serum) for 1st till 28th April?

- Answer _____
- Was the information easy to find? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Task 6: For the same test, what is the aTAT for Routine tests on 12th April?

- Answer _____
- Was the information easy to find? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Task 7: How many Albumin samples were received at 9am on the same day?

- Answer _____
- Was the information easy to find? [Yes / No]
- How confident are you in your answer? [1-5, 5 being the most confident] _____

Appendix E: SUS Questionnaire for TAT Dashboard

Dear Participant,

I am kindly inviting you to take part in a short survey questionnaire on the system usability of the TAT dashboard, which was built for my dissertation in part fulfillment for MSc Digital Health at the University of Malta, under the supervision of Dr Conrad Attard.

This exercise takes no more than 5 minutes to complete. Kindly choose the most appropriate responses for you. Your participation in this study is voluntary and you may stop this questionnaire at any point. Collection of data is anonymous and you may rest assured that you cannot be identified in this survey.

Thanks in advance for your participation in this research.

Yours Sincerely,

Sephora Camilleri

sephora.camilleri.09@um.

edu.mt

* Indicates required question

1. I agree to participate in the usability study of the TAT dashboard conducted by Sephora Camilleri.

I understand that participation in this usability study is voluntary and I agree to immediately raise any concerns or areas of discomfort during the session with the study administrator.

Mark only one oval.

- ◯ Agree
- ◯ Disagree

System Usability Scale

2. I think that I would like to use this system frequently. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

3. I found the system unnecessarily complex. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

4. I think the system was easy to use. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

5. I think that I would need the support of a technical person to be able to use this * system.

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

6. I found the various functions in this system were well integrated. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

7. I thought there was too much inconsistency in this system. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

8. I would imagine that most people would learn to use this system very quickly. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

9. I found the system very cumbersome to use. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

10. I felt very confident using the system. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

11. I needed to learn a lot of things before I could get going with this system. *

Mark only one oval.

	1	2	3	4	5	
Stro	◯	◯	◯	◯	◯	Strongly Agree

12. Do you have any other suggestions or feedback?