AI Feasibility Assessment for a medium sized biotech company that wants to automate their lab scheduling system.

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Background

A medium-sized biotech company located in the Boston area aimed to streamline its complex analytical laboratory operations to achieve greater efficiency. The company's primary goal was to eliminate bottlenecks in lab workflows and achieve a more balanced and efficient utilization of lab instruments among lab operators. The laboratory operates at Biosafety Level 2 (BSL-2) and adheres to GxP standards, ensuring regulatory compliance and quality control.

The lab team handles multiple complex workstreams simultaneously, including routine sample testing, assay development, in addition to qualification and validation activities. Despite having enough instruments, lab personnel frequently experienced scheduling conflicts and bottlenecks, forcing operators to complete projects outside of regular working hours on a frequent basis.

Certain projects were given higher priority for instrument scheduling, such as method qualification, validation activities, timed studies, and sample testing, while research and development tasks were given lower priority. The manual scheduling approach used by lab operators contributed to equipment bottlenecks, delays in experiments, and the suboptimal use of costly lab instruments.

To address these challenges, the organization engaged Accura Bio Solutions to advise on identifying an effective solution. Accura Bio solutions recommended an AI feasibility study for scheduling with the goal to evaluate the likelihood of its success before committing significant resources. Key areas of analysis included technical requirements, data availability and quality, financial considerations and the organization's readiness for change. The projected timeline for this study was 8-10 weeks and the project was structured using a phased approach depicted in **Image 1**.

The project stakeholders were:

- **Sponsor:** the head of R&D who was responsible for strategic alignment and funding approval
- **Lab Operations Manager:** responsible for workflow validation and defining requirements
- **Scientists & technicians:** who contributed to defining user needs, adoption risks, and usability feedback
- **IT team:** Who were responsible for integration, security, and data readiness
- **Finance:** responsible for cost modeling and ROI validation

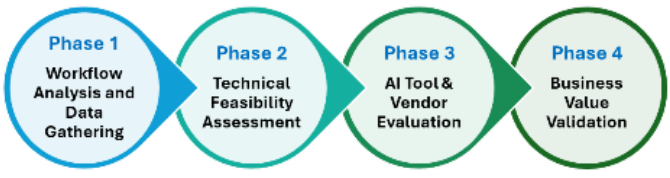

Image 1: This project was structured using a 4-Phase approach starting with the workflow analysis and ending with the business value validation for implementing an AI solution.

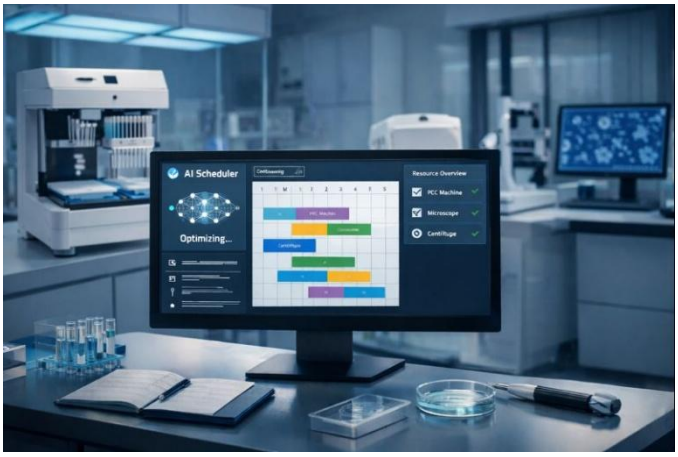

Image 2: A visual depiction of an AI scheduling solution for the lab in this conceptual study.

Phase 1: Understanding the workflow and requirements (1-2 weeks)

During the initial phase of the project, Accura Bio Solutions collaborated closely with the lab team to learn about the lab operations. The primary objective was to comprehensively map out all workstreams and processes associated with lab operations by conducting interviews and collecting all available data sources relevant to instrument scheduling.

The interviews provided insights into the experiment workstreams, the procedures for scheduling instruments, and the system of prioritizing experiments. Through these interviews, the team aimed to identify areas where bottlenecks, pain points, and challenges arose in the scheduling practices. This phase defined the baseline workflow and constraints that could be later used for AI modeling.

The core activities the team conducted were:

- Documenting the existing workflow for lab instrument scheduling
- Finding bottlenecks, pain points, and conflicts that occurred during scheduling
- Gaining an understanding of overall lab workflows, including experimental dependencies, turnaround times, and prioritization methods
- Defining measurable success criteria and metrics for evaluating the scheduling solution

The lab feasibility study evaluated scheduling and usage constraints for the following shared instruments:

- 4x Applied Biosystems qPCRs
- 2x benchtop flow cytometers
- 4x QiaCube nucleic acid purifiers
- 2x droplet digital PCRs
- 1x NGS sequencer
- 2x Spectramax plate readers
- 3x plate washers
- 6x Lab Hoods
- 2x Biomek liquid handlers
- 1x Echo acoustic liquid handler

*Note: Incubators, heaters, shakers, and pipettors were available as needed and were therefore not considered sources of constraint in this study.

Phase 2: Data & Technical Feasibility Assessment (Weeks 3–4)

During the second phase of the project the team reviewed the 6 months of historical scheduling data and equipment usage logs. The data sources included manual scheduling spreadsheets owned by the lab operations team, instrument logs which identify users, start/stop times, errors, and downtime, LIMS data on Experiment IDs, assay types and run duration, and maintenance records and staff schedules. The team also analyzed all the data sources in **Table 1** for data quality and gaps. This step was necessary to understand the technical readiness of the data for adopting an AI solution.

Table 1: Data sources analyzed

Data source	Description	Data Owner
Manual scheduling (spreadsheets, instrument log sheets)	Instrument reservations and time blocks	Lab Operations
LIMS	Experiment IDs, assay type, run duration	IT team
Instrument logs	Start/stop times, runtime errors, downtime	Lab operations
Maintenance records	Equipment servicing: Preventative Maintenance, calibration, downtime	Facilities
Staff schedules	Operator availability and shifts	HR/Lab managers

Activities included:

- Reviewing the past 6 months of historical scheduling data and equipment usage logs
- Assessing data availability, quality, and gaps
- Evaluating integration needs with existing LIMS/ELN systems
- Identifying compliance, security, and governance requirements

A snapshot of the data gathered from this study is shown in **Tables 2-4** for some of the instruments included in this study, notably, representing important categories of instruments with different data usage patterns and metrics.

Table 2: qPCR Instrument Utilization (4 Instruments)
6-month average weekday usage:

Metric	Value
Available hours per instrument	10 hrs/day
Average booked hours	6.5 hrs/day
Actual runtime	5.8 hrs/day
Idle time	2.2 hrs/day
Schedule overruns	~15% of runs
Peak demand	10:00 am – 2:00 pm

Table 3: NGS Sequencer (1 Instrument)

Metric	Value
Available hours	24 hrs/day
Average runs per week	4
Average run duration	30 hrs
Queue wait time	3-5 days
Failed/repeated runs	8%
Maintenance downtime	1 day/month

Table 4: Liquid Handling Systems (Biomek + Echo)

Metric	Biomek (2x)	Echo (1x)
Avg daily usage	7 hrs	4 hours
Setup/changeover time	1-1.5 hrs	0.5 hrs
Dependency conflicts	high	low
Skilled operator required	Yes	No

A key insight from this qPCR data in **Table 2** was that while bookings suggested ~65% utilization, the actual productive runtime was closer to 58% owing to setup delays, no-shows, and over-buffering. Similarly, when analyzing the sequencer data in **Table 3** it became clear that it was underutilized mid-week but overbooked before project deadlines, which indicated poor demand forecasting rather than actual capacity constraints. For the liquid handler data in **Table 4**, the scheduling conflicts arose from shared operator constraints, which were not fully captured in booking tools the operators used.

In order to analyze the quality of the data, the team evaluated the information available within the data and performed a gaps assessment (**Table 5**). They assessed instrument reservation timestamps, actual start and end times from instrument logs, and whether the experiment priority was captured. Furthermore, they assessed the data sources for clear operator assignment and examined logs for downtime and maintenance records. While there were some significant gaps in the data, they concluded that the data was sufficient for a pilot study but would still require normalization and enrichment before it could be used for AI modeling.

They also reviewed the LIMS architecture with the IT team. The LIMS system the company used only supported API-based (read-only) data extraction and there was no real-time instrument connectivity for all equipment vendors. The data security met the internal standards for GxP and IT policies. Hence, an implementable AI solution would have to rely on batch data updates from a daily refresh. The team produced a feasibility risk assessment of an AI solution.

Table 5: Data Quality & Gaps Assessment

Data	Status	Gap
Reservation timestamps	available	No standard format
Actual start/end times	Partially missing in 25% of manual entries.	Missing data – instrument logs do not capture instrument setup times
Experiment priority	Not captured.	Word of mouth interpretation
Operator assignment	Captured on most (75%) instrument logs. Some devices (e.g. QiaCube) use shared log-in.	Missing sufficient data
Maintenance windows	available	Not linked to scheduling

The risk assessment in **Table 6** included the risk of incomplete usage logs, user resistance to a new scheduling system, integration complexity, and potential data drift over time. Based on the analysis, they prepared mitigation strategies to handle risks and created an updated risk register.

Table 6: Risk Analysis

Risk	Impact	Mitigation
Incomplete usage logs	Medium	Manual validation during pilot study
User resistance to new scheduling system	Medium	Early scientist involvement in study
Integration complexity	Low-Medium	Pilot limited to 3-4 instruments
Data drift over time	Low	Monthly model review

From the data gathered in Phase 2 of the project, the team decided to proceed with the next phase of the project evaluating AI tools and vendors. Their justification for moving ahead was that the instrument core utilization and time data existed and that the gaps were manageable within the limited pilot scope of the project. The pilot study would be limited to 3-4 instruments that would depict a lab workflow that frequently faced scheduling conflicts, constraints, and operators forced to work outside of normal hours. More significantly, there was a clear opportunity to improve the instrument utilization by 10-15% with automated scheduling.

Phase 3: AI Tool & Vendor Evaluation (Weeks 5–6)

During this part of the study, the team's objective was to identify AI-enabled scheduling solutions that could address lab workflow scheduling complexity and data constraints, while maintaining adherence to regulatory requirements, and to recommend a short list of vendors or solution approaches for a pilot study.

Based on Phase 2 findings, the team defined three viable solution paths:

1. Commercial AI Lab Scheduling Platforms
    - Pre-built tools with configurable scheduling rules
    - Faster deployment, lower technical risk
2. Custom AI Model Integrated with Existing Systems
    - Tailored optimization logic
    - Higher development cost and timeline risk
3. Hybrid Approach
    - Commercial platform with custom rules layered on top
    - Balanced flexibility and speed

After evaluating all paths, the team decided to prioritize commercial or hybrid solutions for pilot feasibility due to limited level of data maturity and timeline constraints of the study. The vendor categories they assessed were AI-based lab scheduling and resource optimization tools and LIMS vendors that offer AI/advanced scheduling modules.

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The team shortlisted vendors based on the following criteria:

- Ability to model multi-instrument dependencies
- Support for operator and skill constraints
- Integration with LIMS/ELN (API availability)
- Configurability without heavy custom coding
- Biotech and GxP readiness

Outcome:

In turn, they shortlisted 3–4 vendors for a detailed evaluation. The vendors were evaluated using real lab scenarios derived from Phase 2 data. They evaluated solutions based on the ability to handle constraints (equipment, operator, and prep time), ability to dynamically reschedule runs that go overtime, priority-based queuing and schedule forecasting. Additionally, they used "What-if" scenario modeling to examine how the solution performs in different real-world situations.

They also assessed the vendors for compliance to ensure the proper data access controls, user roles and audit logs for schedule changes were in place. Furthermore, they assessed that the solution met the validation requirements for regulated environments and the support infrastructure available for SOPs and documentation (**Table 7**)..

Table 7: Technical & Data Compatibility Assessment Criteria

Area	Focus for Evaluation
Data ingestion	Batch vs. real-time support
Data formats	CSV, API, LIMS connectors
Model transparency	Explanations on how scheduling decisions are made
Scalability	Ability to support additional instruments, and labs
Security	Controlled access, audit trails

In addition, they assessed the vendors for costs associated with licensing, implementation, and scalability and any additional costs for training, service and support as depicted in **Table 8**. The initial pilot cost estimate was determined.

Estimate (Pilot):

- Upfront costs: $50K–$80K
- Annual licensing: $30K–$60K

Table 8: Cost Evaluation

Cost	Considerations
Licensing	Per instrument or enterprise
Implementation	Configuration, integration
Support	SLA, training
Scalability	Cost growth and expansion

As part of Phase 3 deliverables, the team produced a vendor evaluation scorecard, a technical integration assessment, a

cost comparison and ROI impact update, and an updated risk register. Based on these assessments, they recommended a pilot vendor.

To move to the next stage of the process, the pilot vendor had to be approved by the stakeholders, and the pilot scope and success metrics were predefined.

Phase 4: Business Value Validation & ROI Analysis (Weeks 7–8)

During the final phase of the feasibility study, the team quantified the expected business impact of an AI-enabled lab scheduling solution within a limited pilot study scope and validated whether the investment would be justified relative to cost, risk, and operational benefit.

The pilot scope definition included two qPCR instruments, one Biomek liquid handler, and one NGS sequencer (**Image 3**). The workstreams covered under this pilot were routine sample testing, method qualification and validation, and timed studies. However, exploratory research and development activities, as well as comprehensive multi-site scheduling, were specifically excluded from the pilot scope.

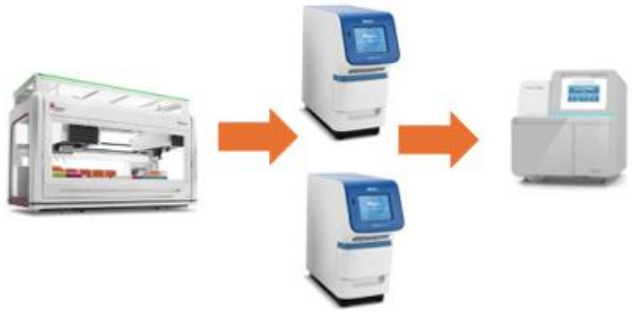

Image 3: Workstream chosen for the pilot study for a NGS library prep workflow with 4 lab instruments that often face scheduling conflicts and bottlenecks.

The team began by evaluating their current baseline performance (**Table 9**). The baseline metrics were validated through the scheduling logs, interviews with lab personnel, and instrument usage data collected in Phases 1 and 2. Then they forecasted the expected improvements for the pilot project based on vendor benchmarks, internal data modeling and conservative assumptions (**Table 10**).

Table 9: Baseline performance metrics

Metric	Current state
Avg instrument utilization	55-65%
Avg experiment wait time	1.8 days
Schedule overruns	15% of runs
Missed deadlines	10% of projects
Scientist Idle time	1 hr/day
After-hours instrument usage	Frequent (unplanned)

Table 10: Expected Performance Improvements (Post-AI Scheduling)

Metric	Expected Improvement
Instrument Utilizaton	10-15% increase
Experiment wait time	30-40% decrease
Schedule overruns	<5%
Missed deadlines	<3%
Scientist Idle time	30-45 min/day decrease
After hours work	Significantly reduced

The key drivers of expected improvement were priority-based automated scheduling, in-built buffer room for experiment setup, automated handling of operator constraints (e.g. deadlines), reduction of idle-time due to over-buffering, and finally dynamic rescheduling if experiments overrun.

As a final step of the feasibility study, the team conducted a financial analysis to evaluate the costs and estimate the potential ROI of implementing the pilot study of the AI solution. The financial analysis was driven by three cost drivers, cost savings from increased productivity, cost savings from delayed purchase of new capital equipment and operational risk reduction from project delays and missed timelines. **Table 11** and **Table 12** provide the cost and ROI summaries.

Financial Impact Analysis (annualized improvements)

Cost savings from productivity gains

- 20 lab operators
- Average time 0.5 hours/day saved
- Annual labor value recovered: $150,000 - $200,000

Instrument Utilization

- Improved utilization delays need capital equipment purchases
- Avoid major instrument purchase over 3 years
- Estimated value: $250,000 - $400,000

Operational Risk Reduction

- Fewer missed deadlines for validation and qualification activities
- Reduced risk of project delays impacting regulatory deadlines

Table 11: Cost Summary

Cost Category	Estimated Cost
Pilot implementation	$50K - $80K
Annual licensing	$30K - $60K
Internal effort (IT, Lab Ops)	$20K
Total Year 1 Cost	**$100K - $160K**

Table 12: ROI Summary

Metric	Estimated Benefits
Annualized quantified benefits	$250K - $400K
Payback period	6-12 months
3-year ROI	150-250%
Intangible benefits	Reduced burnout, improved compliance, better planning predictability

Conclusion:

Even under conservative assumptions, the AI-enabled scheduling solution is expected to deliver a positive ROI within the first year and provided significant operational benefits. The

team defined the success metrics for the pilot study as shown in **Table 13**.

Table 13: Pilot Success Metrics

Category	KPI
Utilization	10% or more increase
Scheduling conflicts	50% or more reduction
Equipment wait time	30% or more reduction
Compliance	No audit findings

Change Management & Adoption Plan
In order to prepare for the pilot study the team created a change management and adoption plan. Significantly, the team planned to involve scientists and lab operators early in the process to ensure they are part of the decision-making process, can evaluate and understand the changes in operation. Furthermore, the team will provide training and update SOPs to ensure everyone is prepared for the transition. To facilitate a smooth changeover, manual and AI scheduling will be run in parallel for two weeks, while weekly feedback sessions are held to address concerns and gather input.

Final Recommendations:
The feasibility study outcome showed that the AI pilot is technically feasible, operationally practical, and financially sound for a medium-sized GxP biotech lab. The recommended next steps are to launch a limited pilot using the commercial AI-based scheduler chosen for the pilot study and to measure the results against the predetermined metrics. If the outcomes are positive and fulfill the predefined success criteria, the next step will be to scale up the implementation to involve the full lab operations including all the lab workstreams. Additionally, governance structures will need to be adapted and put place for ongoing updates, validation, and compliance.