

AI Lab Transition Strategy — Detailed Overview

Three Pillars Per Phase: Technology · Organisation & Culture · Data Supply

PHASE	TECHNOLOGY	ORGANISATION & CULTURE	DATA SUPPLY	KEY METRICS
Phase 0 Data Readiness Human decides Digital records	Instrument data capture Machine-readable formats Metadata standardisation Assay, project, site consistency Experiment-result linkage Done → outcome → meaning Ontology adoption BAO, ChEBI, OBI mapping LIMS · ELN · Integration	Leadership sponsors data as priority Not delegated to IT Lab champions (2–3 per group) Peer-credible senior scientists Data quality ownership defined Scientist vs. manager vs. steward ■ Data Practices & Attitudes Survey ■ Expect passive non-compliance on data entry	Audit captured vs. generated data 30–60% of instrument output typically lost Prospective capture design Env, reagent lot, calibration data External ontology mapping Lightweight, high interop impact Data quality baseline Error rates, completeness, consistency	>90% structured data capture Cross-team query volume ↑ Metadata completeness % Survey Δ vs. baseline
Phase 1 Predictive Intelligence Human decides ML recommends	Assay performance prediction Yield, variability, failure probability Instrument drift detection Predictive maintenance Compound-property prediction ADMET, solubility, stability Experiment prioritisation / DoE XGBoost · TxGemma · Local models · SPC	"Trust but verify" posture Leadership endorses, doesn't mandate ML literacy training Evaluate outputs, not build models Accountability framework Who owns a bad ML-informed decision? ■ AI Readiness & Trust Survey (quarterly) ■ "The model is wrong" — handle constructively	Labelled training data (bottleneck) Retrospective + prospective labelling New data streams required Env monitoring, reagent lots, operator External datasets ChEMBL, PubChem, BindingDB Volume reality check Small n → classical ML, not deep learning	Model accuracy vs. actuals per model Adoption % predictions consulted Downtime ↓ unplanned instrument Trust Δ quarterly survey trend
Phase 2 Augmented Workflows Human approves LLM agents draft	Protocol & document drafting SOPs, deviations, stability reports Literature-informed design (RAG) Internal + external corpus NL query over lab databases Cross-system data access Equipment troubleshooting Frontier LLMs · Fine-tuned SLMs · RAG · MCP	Explicit AI authority boundaries Documented by leadership AI Review Board established Science, quality, IT, regulatory AI output review skills training Agent errors ≠ human errors ■ Workflow Impact & Autonomy (quarterly) ■ Approval fatigue + "It'll take my job" fears	Curated RAG corpus SOPs, protocols, records — kept current Agent interaction logs Prompt, output, review, edits External literature access PubMed, bioRxiv, regulatory guidance IP governance framework Which models see which data	>70% draft acceptance rate Hallucination rate tracked Review time ↓ may = fatigue ■ Role Δ autonomy survey
Phase 3 Bounded Autonomy AI decides within guardrails	Automated parameter adjustment Within validated ranges Dynamic experiment scheduling Resource + priority optimisation Automated QC triage Flag / hold / release by criteria Predictive inventory ordering Orchestrated agents · Validated decision engines	Delegated decision authority Leadership accepts AI outcome liability Role redesign Scientist → exception handler & auditor QA/Regulatory co-design Architects of guardrails, not reviewers ■ Post-Autonomy Impact (per use case) ■ QA/Reg resistance: "How do we audit this?"	Real-time data feeds (not batch) Live instrument, inventory, scheduling High-volume decision logs Trigger → input → output → outcome External operational feeds Supplier lead times, regulatory calendar Closed-loop feedback data Continuous validation & drift detection	>95% decision accuracy Zero scope creep incidents Intervention rate monitored Confidence Δ post-autonomy survey

■ Technology alone does not deliver AI transitions. Every phase requires parallel investment in culture, leadership behaviour, and data supply.