Fair Contextual Bandits for Equitable Diagnostic Decision-Making Under Missing Context

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This project will develop a practical, reproducible framework for **contextual multi-armed bandits** (iC-/C-MABs) to make sequential decisions under uncertainty and limited resources while treating **algorithmic fairness** as a first-class objective. The work on this generic framework focuses on measuring and improving fairness across the clinical (diagnostic-like) and quantum domains, through the following deliverables: i) a simulation-first diagnostic-like sequential decision environment with controllable context missingness/uneven measurement and distribution shift, ii) a fairness aware and contextual MABs evaluation stack (baselines + contextual policies) with time-evolving group disparity reporting and at least one mitigation mechanism, and iii) a transfer study demonstrating the same policy stack in a quantum-routing simulator.

The goal is to build a **novel integration**: evaluating fairness aware and contextual MABs policy choices in both domains, while reporting and mitigating fairness disparities **over time** rather than only post-hoc.

Background: Many real-world workflows in both clinical diagnostics and quantum-routing require sequential choices under uncertainty, resource constraints, and distribution shift. These settings can amplify inequities when some groups systematically have lower-quality context or different error profiles. This proposal frames this as a contextual bandit problem: at each step, choose an action (an "arm") given observed context to maximize utility while controlling fairness gaps. In both domains, multi-armed bandits formalize online decision-making with exploration–exploitation tradeoffs, and contextual bandits condition decisions on side information that can improve sample-efficiency and stability. In the quantum-routing domain, context may include link-quality estimates, network load/queue signals, and qubit availability/quality, but these signals can be delayed, noisy, or partially observed. In the clinical diagnostics domain, context may include patient features, test and sample-quality indicators, and operational constraints, but access to context can be incomplete or systematically noisier for some populations. These limitations create performance and fairness risks, especially when optimizing aggregate performance, which can hide subgroup error spikes (e.g., false-negative gaps) unless the system is explicitly monitored and constrained.

Unlike prior work that often reports utility-only bandit performance or post-hoc fairness for static predictors, this project makes the time-evolving utility–fairness tradeoff explicit and tests transfer across both testbeds.

Scientific Merit: The core scientific question across the clinical diagnostics and quantum-routing domains is: *when does informative context (and how it is modeled) materially reduce disparity and error in sequential decision-making under shift?* This is challenging in both domains because (1) feedback is partial and delayed (only the chosen test/routing action reveals an outcome), (2) conditions shift over time (patient mix and operational processes; network load and link/qubit conditions), and (3) fairness constraints can conflict with pure utility optimization.

This proposal draws on contextual bandit methods for sequential decision-making with side information [3, 4] and on the algorithmic fairness work that defines and measures group-based error disparities [5]. Practically, it builds on an existing quantum-routing simulator and previous work on *Equitable Bioinformatics* [2], operationalizing fairness audits and mitigation for diagnostic-relevant pipelines. The key innovative component is the two-domain evaluation: treating the **quantum-routing environment** as a first-class testbed alongside the diagnostic-like simulation, using the same fairness-aware contextual bandit stack in both to test robustness and transfer across radically different domains.

Broader Impacts: If successful, this work provides a concrete, reproducible framework for fairness-aware sequential decision systems in diagnostics and other public-health settings (including COVID-style test allocation) where both resources and context quality are limited. It also advances trustworthy learning-based control in quantum-routing by adding explicit disparity monitoring and constraints to online routing/allocation policies, producing reportable utility–fairness tradeoffs under shift. For this project, the result is a reusable evaluation harness (two testbeds + shared policy API) that supports advisor-driven experimentation and future publication-quality benchmarking of fairness-aware bandit policies.

Approach: The goal is to implement and evaluate fairness aware and contextual MABs policies across two testbeds (diagnostic-like sequential decision simulation + quantum-routing simulator), and to report utility–fairness tradeoffs under shift. The work is structured to be feasible without sensitive clinical data access (simulation-first), while remaining extensible to approved open datasets. The tasks are:

- **Build diagnostic testbed:** implement a sequential decision simulation (test/model choice, retesting, pipeline choice) with distribution shift and controllable context missingness/uneven measurement.

- **Build quantum testbed:** integrate policies into the quantum-routing simulator; define flow/node groups and track service equity across groups.

- **Implement bandit policies:** non-contextual baselines (epsilon-greedy, UCB, Thompson), a contextual baseline (LinUCB-style), and one informed contextual (iCMAB-style) policy under a shared interface.

- **Define reward + metrics:** utility with explicit cost/latency and safety weighting; report regret/utility plus time-evolving fairness metrics (group-wise FNR/FPR gaps and at least one additional criterion).

- **Add fairness mitigation:** implement one fairness-aware mechanism (constraint/penalty or calibration) and quantify utility–fairness tradeoffs across both testbeds.

- **Package for reproducibility:** Python 3.11+ modular scripts (not one notebook), fixed seeds + configs, and a minimal test suite (sanity checks for simulations and metric computation).

Phase 1 includes environment + baselines + initial fairness audit/mitigation; Phase 2 includes robustness under shift + ablations + packaging for code review and final report/demo.

References:

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