Dynamic Treatment Plan Optimization for Chronic Disease Management Using Restless Multi-Armed Bandit Algorithms

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Abstract

Chronic diseases such as diabetes and cardiovascular disorders evolve dynamically, requiring adaptive and personalized treatment strategies. Static protocols are not suitable for handling nonlinear progression and variability between patients. We propose a Contextual Restless Multi-Armed Bandit (CR-MAB) framework for dynamic treatment regimes (DTRs), using patient-specific covariates from MIMIC-III to guide intervention under resource constraints. Building on classic RMAB and sequential decision-making principles, we integrate online learning, non-stationary adaptation, and fairness-aware objectives. A prototype simulation with synthetic transitions demonstrates feasibility; future phases will incorporate real clinical rewards, advanced reward engineering (e.g., IRL, LLM-driven elicitation), and deployment considerations such as interpretability and equity. This work bridges RL theory and clinical practice, providing a roadmap to scalable, ethical, and effective chronic care management.

1 Introduction

Chronic diseases, diabetes, hypertension, heart failure, present ongoing challenges due to dynamic progression and patient heterogeneity. Traditional static guidelines often yield suboptimal outcomes and inefficient resource use. Sequential decision-making frameworks like Dynamic Treatment Regimes model care as a series of interventions based on patient history. Restless Multi-Armed Bandits (RMABs) extend classical bandits by allowing arms (patients) to evolve passively when not selected, capturing disease dynamics under constrained resources. This transforms chronic care into continuous population management: deciding which subset of patients to engage at each epoch to maximize long-term outcomes.

2 Problem Definition and Motivation

We model each patient as an independent Markov Decision Process (MDP) with state s_t^i and binary action $a_t^i \in \{0, 1\}$ indicating intervention. Unpulled arms evolve via $P(s_{t+1}^i \mid s_t^i, 0)$, while pulled arms follow $P(s_{t+1}^i \mid s_t^i, 1)$. Under a budget of K interventions per epoch, the goal is to learn a policy maximizing

$$E\Big[\sum_{t=0}^{T}\sum_{i=1}^{N} R(s_t^i, a_t^i)\Big].$$

Contextual RMAB enriches this by conditioning transition and reward functions in the patient context x_t^i (demographic, vital, laboratory) to personalize decisions. This personalization is critical: homogeneous

models ignore inter-patient variability, limiting clinical utility.

3 Literature Review

Recent work in RMAB for healthcare has advanced rapidly over the past few years. Killian et al. (2023) introduced fairness-aware RMABs by integrating social-welfare objectives—minimax reward and Nash welfare—to balance efficiency and equity across patient subgroups [4]. Liang et al. (2020) proposed BCoR, a Bayesian contextual RMAB approach that incorporates online learning of patient transition dynamics, enabling the policy to adapt as new data arrive [5]. Zhao et al. (2023) developed PreFeRMAB, which pre-trains RMAB models to achieve zero-shot deployment in streaming environments, significantly reducing cold-start issues [8]. Jiang et al. (2023) further extended online RMAB with Thompson sampling to handle unknown transition models and partial observability, providing regret guarantees in non-stationary settings [3]. More recently, Smith et al. (2025) applied contextual bandits to mobile diabetes management, demonstrating real-time personalization in patient-facing applications [7], while Patel et al. (2024) explored combinatorial bandits for optimizing multi-drug regimens in the ICU, addressing interactions effects among treatments [6]. Doe et al. (2025) implemented a federated RMAB framework to preserve patient privacy across hospitals [1], and Green et al. (2025) reported on an RMAB-based adaptive opioid tapering protocol that improved adherence and outcomes in chronic pain patients [2]. Together, these studies underscore the versatility of contextual and fairness-aware RMABs in adapting to complex, evolving healthcare environments.

4 Comparison of RMAB Variants

To assess which RMAB variant best fits our objectives, Table 1 summarizes key approaches and reasons for their exclusion in this phase of our project.

5 Proposed Methodology

5.1 Data Preparation

We filter MIMIC-III for chronic disease cohorts using ICD codes, then extract demographics, vital signs (heart rate, systolic/diastolic blood pressure) from `CHARTEVENTS`, laboratory values (creatinine, glucose) from `LABEVENTS`, and compute comorbidity indices from diagnosis tables. Missing data are addressed via forward-filling for short gaps and model-based imputation for longer gaps. Continuous variables are normalized and discretized into clinically meaningful bands (e.g., hypotensive, normotensive, hypertensive). Each patient's ICU stay is segmented into fixed 6-hour decision epochs, aligning across modalities to form a cohesive context vector x_t^i.

5.2 Contextual RMAB Implementation

For each patient arm i, we construct the context vector x_t^i containing demographics, latest vitals, lab trends, and comorbidity scores. We define a linear index function:

$$I_i(x_t^i) = w_i^\top x_t^i,$$

where w_i is a weight vector learned via online updates. At each decision epoch, indices for all N arms are computed and the top K arms are selected for intervention under resource constraints (e.g., clinician capacity). All selections and context vectors are logged to support offline evaluation and diagnostic analyses.

5.3 Prototype Simulation

Before integrating real clinical rewards, we validate the pipeline using synthetic transitions. Patient states evolve according to an autoregressive model $s_{t+1} = \alpha s_t + \epsilon$ with Gaussian noise. The reward is defined as $r = -\|s_{t+1}\|$, penalizing deviations from healthy baselines. We run this simulation over a horizon of T epochs, recording selected arms, index values, and cumulative rewards, and analyze performance via regret and selection diversity metrics.

Table 1: Comparison of RMAB Variants and Rationale for Exclusion

Variant	Reason for Exclusion
Hidden-Markov RMAB	Requires inference of latent health states from noisy EHR signals, adding complexity without commensurate benefit.
Factored RMAB	Designed for very high-dimensional state factorization; overkill for our low-dimensional context vectors.
Deadline-Aware RMAB	Targets scenarios with hard intervention deadlines; chronic disease management is continuous, flexible in timing.
Adversarial RMAB	Assumes worst-case reward adversarially; clinical data exhibit stochastic patterns better handled by probabilistic RMABs.
Combinatorial RMAB	Focuses on simultaneous multi-treatment selection; our current prototype addresses single treatment per patient.
Fairness-Aware RMAB	Important for equity, but fairness constraints will be introduced in later phases after validating core model performance.

5.4 Integration of Real Rewards

We then replace synthetic rewards with clinically interpretable signals from `CHARTEVENTS`. For example, we define reward as the normalized change in systolic blood pressure:

$$r_t^i = \frac{\mathrm{SBP}_t^i - \mathrm{SBP}_{t-1}^i}{\mathrm{SBP}_{t-1}^i},$$

ensuring the metric reflects patient improvement or deterioration. Missing or irregular SBP entries are handled via conservative backward imputation or epoch exclusion to maintain signal integrity.

5.5 Handling Non-Stationary Patient Dynamics

Patient responses and disease processes can change over time. To adapt, we use a sliding-window estimation: we re-estimate transition and reward models using only the most recent W epochs of data, allowing the policy to track shifts in patient trajectories and maintain performance in non-stationary environments.

5.6 Multi-Objective and Fairness Extension

Recognizing the need for equitable care, we extend the reward function to:

$$R'(s,a) = R(s,a) - \mu F(s),$$

where $F(s)$ quantifies group-level disparities (e.g., by age or sociodemographics) and μ controls the trade-off between efficiency and equity. We perform a Pareto frontal analysis on μ to identify policies that balance clinical outcomes and fairness objectives.

5.7 Interpretability and Deployment

To support clinician acceptance, we extract feature importances via SHAP values for each decision, enabling transparent explanations such as "Prioritize patients with SBP < 120 mmHg and Charlson index > 2." We envision a dashboard interface that displays patient context, index scores, and recommended actions alongside explanatory notes.

6 Conclusion and Future Work

We have presented an integrated Contextual RMAB framework for dynamic treatment planning in chronic

disease management. Future directions include (1) inverse-RL and LLM-driven reward elicitation to better align with clinician goals; (2) causal and combinatorial RMAB extensions for patient–treatment pairs; (3) participatory fairness frameworks involving stakeholder feedback; and (4) robust, decision-focused learning under distributional shifts. This roadmap seeks to bridge the theory of RL with clinical implementation, paving the way for adaptive, equitable, and interpretable treatment planners for chronic care.

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