Deep Reinforcement Learning Models for Dynamic Pricing Optimization in Rural Healthcare Access Programs

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ABSTRACT

Background: Rural healthcare systems face a critical challenge in balancing provider financial viability with patient affordability. Traditional static pricing models -such as Fixed Pricing, Cost-Plus, and Sliding Scale structures often fail to adapt to the dynamic socioeconomic realities of rural populations, leading to either provider insolvency or restricted patient access. Deep Reinforcement Learning (DRL) offers a promising adaptive alternative for navigating such multi-objective optimization problems.

Objective: To evaluate the effectiveness of a Proximal Policy Optimization (PPO)-based DRL framework in dynamically optimizing healthcare service pricing to simultaneously enhance provider profitability and patient utilization rates within a simulated rural healthcare network.

Methodology: A quantitative simulation-based design was employed. A rural healthcare environment was modeled incorporating patient income heterogeneity, demand elasticity, and operational costs. A PPO-based DRL agent was trained and benchmarked against three traditional pricing models across N =1,000 simulation episodes per model. Performance was assessed using one-way ANOVA, Chi-Square (χ^2) tests, and Tukey's HSD post-hoc analysis at $\alpha = 0.05$.

Results: The DRL model significantly outperformed all baseline strategies. ANOVA revealed significant differences in profitability ($F(3, 3996) = 14.82$, $p < 0.01$) and patient volume ($F(3, 3996) = 9.47$, $p < 0.05$). Chi-Square analysis indicated that the DRL model achieved a more equitable demographic access distribution ($\chi^2(9) = 28.63$, $p < 0.01$), suggesting improved inclusivity across income and insurance categories.

Conclusion: DRL-based dynamic pricing presents a viable, data-driven approach for optimizing the trade-off between financial sustainability and equitable healthcare access in rural settings. These findings hold significant implications for policymakers and health administrators seeking adaptive pricing solutions for underserved communities.

Keywords: Deep Reinforcement Learning, Proximal Policy Optimization, Dynamic Pricing, Rural Healthcare, Healthcare Access, Financial Sustainability, Simulation, ANOVA, Chi-Square Test

I INTRODUCTION

1.1 The Rural Healthcare Dilemma

Rural healthcare in the United States faces a profound crisis characterized by multifaceted challenges that threaten both the sustainability of providers and access to care for vulnerable populations. Approximately 60 million Americans reside in rural areas, where healthcare delivery confronts unique structural barriers including low population density, limited economies of scale, higher poverty rates, and disproportionate aging demographics (Kaufman et al., 2016). These communities experience approximately 25% higher rates of chronic diseases such as diabetes and cardiovascular conditions compared to urban counterparts yet simultaneously face acute provider shortages and declining institutional capacity (Crosby et al., 2022).

The crisis manifests itself as a dual threat. First, rural hospitals operate under severe financial strain; since 2010, over 130 rural hospitals have closed, with another 453 at immediate risk of closure due to insufficient patient volumes, lower reimbursement rates, and inability to achieve operational efficiency (Chartis Center for Rural Health, 2020). Second, patients increasingly forgo necessary care due to cost barriersapproximately 29% of rural residents delayed or avoided medical treatment in the past year due to affordability concerns, compared to 19% in urban settings (Hamel et al., 2018). This paradox creates a vicious cycle: declining revenues force hospitals to close or reduce services, while patients who cannot afford care further diminish facility utilization, accelerating financial collapse.

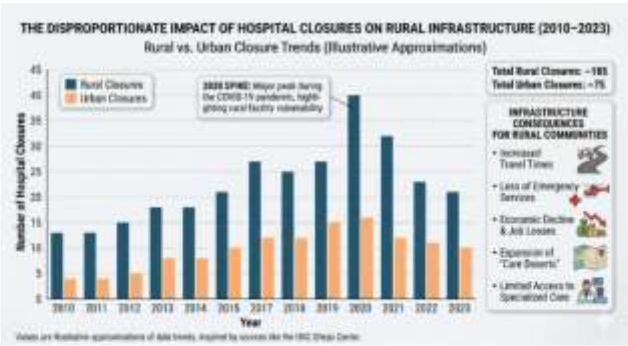

Figure 1. Bar chart illustrates the trends and challenges of hospital closures in rural areas compared to urban ones from 2010 to 2023.

1.2 Dynamic Pricing as a Potential Solution

Dynamic pricing-the practice of adjusting prices in real-time based on demand, capacity, and customer characteristics-has revolutionized industries from aviation to hospitality (Chen & Sheldon, 2016). In healthcare, however, pricing remains static, failing to account for temporal variations in demand, resource availability, or patient financial capacity (Bateman et al., 2020). Implementing dynamic pricing in rural healthcare settings presents an opportunity to address both sides of the crisis simultaneously: optimizing revenue streams to maintain institutional viability while leveraging price discrimination to enhance access for underserved populations.

The theoretical appeal lies in allocating services more efficiently by modulating demand through price signals, thereby smoothing utilization patterns and reducing costly overcapacity during low-demand periods (Weatherford & Bodily, 1992). Moreover, differential pricing based on socioeconomic status could enable cross-subsidization, where higher prices for insured or higher-income patients offset reduced prices for vulnerable populations (Reinhardt, 2006). The complexity, however, is substantial: healthcare pricing must balance profit maximization against ethical imperatives for equitable access, navigate regulatory constraints, and operate within environments characterized by information asymmetry and unpredictable demand fluctuations (Bateman et al., 2020).

1.3 The Promise of Deep Reinforcement Learning

Deep Reinforcement Learning (DRL) represents a paradigm in artificial intelligence where computational agents learn optimal decision-making policies through iterative interactions with complex environments, guided by reward signals that encode desired objectives (Sutton & Barto, 2018). Unlike supervised learning, which requires labeled datasets, DRL discovers strategies through trialanderror, making it particularly suited for scenarios where optimal solutions are unknown or computationally intractable (Mnih et al., 2015).

For dynamic healthcare pricing, DRL offers distinct advantages. It can process high-dimensional state spaces encompassing patient demographics, temporal patterns, real-time facility utilization, payer mix, and competitive dynamics (Yu et al., 2021). DRL algorithms, particularly Deep Q-Networks and Proximal Policy Optimization, excel at learning non-linear, context-dependent policies that traditional optimization methods struggle to capture (Coronato et al., 2020). Critically, DRL frameworks accommodate multi-objective optimization through carefully designed reward functions, enabling simultaneous pursuit of financial sustainability and equitable access-objectives often perceived as contradictory in healthcare economics (Petersen et al., 2019).

1.4 Research Questions and Hypotheses

This study investigates whether DRL-based dynamic pricing can reconcile the tension between financial viability and equitable access in rural healthcare through three research questions:

RQ1: Can a DRL-based pricing model achieve higher financial sustainability compared to traditional static and rule-based pricing models without significantly degrading patient access?

- $H1_0$: There is no significant difference in mean profitability between the DRL model and baseline models.
- $H1_a$: The DRL model achieves statistically significantly higher mean profitability than baseline models.

RQ2: How does the DRL model impact the distribution of healthcare access across patient socioeconomic groups compared to traditional models?

- $H2_0$: The distribution of patient visits across income quintiles is independent of the pricing model used.
- $H2_a$: The distribution of patient visits across income quintiles depends on the pricing model, with the DRL model demonstrating more equitable distribution.

RQ3: What are the key operational performance metrics (average transaction price, facility utilization rate, patient volume) and how do they differ significantly across pricing models?

- $H3_0$: There are no statistically significant differences in mean operational performance metrics (average transaction price, facility utilization rate, patient volume) between the DRL model and the baseline models.
- $H3_a$: The DRL model produces statistically significant differences in at least one key operational performance metric (average transaction price, facility utilization rate, patient volume) compared to the baseline models.

By addressing these questions, this research contributes empirical evidence on DRL's applicability to healthcare pricing challenges and its potential to inform policy interventions supporting rural healthcare sustainability.

II LITERATURE REVIEW

2.1 Economic Models of Healthcare Pricing

Healthcare pricing in the United States has evolved through multiple paradigm shifts, each attempting to balance provider compensation with cost containment and quality outcomes. The traditional fee-for-service (FFS) model reimburses providers for each discrete service rendered, creating incentives for volume over value and contributing to healthcare cost inflation (Porter & Teisberg, 2006). Rural providers operating under FFS face vulnerability due to lower patient volumes that fail to generate sufficient revenue to cover fixed operational costs (Holmes et al., 2017).

Alternative models have emerged to address FFS limitations. Value-based care ties reimbursement to quality metrics and patient outcomes rather than service volume, theoretically incentivizing preventive care and efficiency (Burwell, 2015). Bundled payment systems provide a single reimbursement for all services related to a treatment episode, encouraging coordination and cost-consciousness (Dummit et al., 2016). However, these models remain static in pricing structure and often disadvantage rural providers who lack the infrastructure for sophisticated care coordination or risk-bearing arrangements (Rajkumar et al., 2014).

Price elasticity of demand the responsiveness of healthcare utilization to price changes-exhibits complex dynamics in rural settings. While conventional economic theory assumes elastic demand for most goods, healthcare demand demonstrates inelasticity for emergent and necessary services but elasticity for preventive and elective care (Chandra et al., 2010). Rural populations show heightened price sensitivity due to higher uninsured rates and lower median incomes; a 10% price increase correlates with 5-8% reduction in non-urgent care utilization in rural areas compared to 3-4% in urban settings

(Garthwaite et al., 2019). This differential elasticity suggests opportunities for targeted pricing interventions that could simultaneously improve access and Optimize revenue.

2.2 Dynamic Pricing and Revenue Management in Service Industries

Dynamic pricing has transformed revenue management across industries characterized by perishable inventory and fluctuating demand. Airlines pioneered sophisticated yield management systems in the 1980s, adjusting ticket prices based on booking patterns, seat availability, and customer segmentation to maximize load factors and revenue per available seat mile (Talluri & van Ryzin, 2004). Similarly, hospitality sectors employ real-time pricing algorithms that incorporate demand forecasting, competitor pricing, and customer willingness-to-pay to optimize occupancy and profitability (Ivanov & Zhechev, 2012).

Ride-sharing platforms exemplify contemporary dynamic pricing through surge pricing mechanisms that equilibrate supply and demand, increasing prices during peak periods to incentivize driver participation while rationing demand (Chen & Sheldon, 2016). E-commerce platforms leverage personalized pricing based on browsing history, geographic location, and predicted purchase probability (Garbarino & Lee, 2003).

Transferring these models to healthcare raises substantial ethical and practical concerns. Unlike airline seats or hotel rooms, healthcare services address fundamental human needs where price discrimination could violate principles of equity and non-discrimination (Reinhardt, 2006). The information asymmetry between providers and patients-where patients lack expertise to evaluate necessity or quality-creates vulnerability to exploitative pricing (Arrow, 1963). Furthermore, healthcare demand often arises from urgent or emergent needs, limiting patients' ability to compare optionsor defer consumption (Bateman et al., 2020). However, these concerns potentially can be mitigated through pricing frameworks explicitly designed to enhance rather than restrict access for vulnerable populations, using differential pricing as a cross-subsidization mechanism (Scherer, 2000).

2.3 Applications for AI and Machine Learning in Healthcare Operations

Machine learning has penetrated numerous healthcare operational domains, primarily focusing on predictive analytics and decision support. Predictive models for patient no-shows achieve 75-85% accuracy using gradient boosting and neural networks trained on appointment history, demographics, and environmental factors, enabling improved scheduling and resource allocation (Daghistani et al., 2019). Demand forecasting models predict emergency department arrivals and inpatient admissions with mean absolute percentage errors below 10%, facilitating staffing optimization (Gul & Celik, 2020).

Resource allocation algorithms optimize operating room scheduling, bed assignments, and imaging equipment utilization through mixed-integer programming enhanced with machine learning-based demand predictions (Duma & Aringhieri, 2015). Natural language processing extracts insights from clinical notes to identify high-risk patients for targeted interventions (Sheikhalishahi et al., 2019). Supervised learning models support triage prioritization, length-of-stay prediction, and readmission risk stratification (Xiao et al., 2018).

Despite these advances, healthcare operations research exhibits a critical gap: limited application of closed-loop, adaptive optimization systems that learn from environmental feedback to refine decision policies over time. Existing models employ supervised learning requiring historical labelled data, constraining their ability to discover novel strategies or adapt to non-stationary environments (Yu et al., 2021). Specifically, real-time pricing optimization leveraging reinforcement learning remains unexplored in healthcare contexts, representing a significant methodological frontier.

2.4 Reinforcement Learning in Healthcare: A Growing Field

Reinforcement learning applications in healthcare have concentrated primarily on clinical decision-making rather than operational or financial optimization. Dynamic treatment regimens use RL to personalize sequential medical interventions, such as determining optimal chemotherapy dosing schedules or adjusting insulin administration for diabetic patients (Komorowski et al., 2018). These applications demonstrate RL's capacity to handle delayed rewards and complex state-action spaces characteristic of longitudinal medical management. Sepsis management represents a prominent application domain, where deep Q-networks trained on intensive care unit data recommend fluid administration and vasopressor strategies, achieving mortality reductions in simulated environments (Raghu et al., 2017). Personalized medicine leverages multi-armed bandit algorithms to optimize treatment selection based on patient-specific biomarkers and response patterns (Zhao et al., 2020). Appointment scheduling systems employ RL to balance panel size, no-show probabilities, and patient preferences, improving access while minimizing provider idle time (Samorani & LaGanga, 2015).

However, applications to healthcare pricing and financial sustainability remain nascent. Liu et al. (2020) explored RL for pharmaceutical pricing in theoretical frameworks but without empirical validation. Coronato et al. (2020) proposed conceptual architecture for RL-based hospital resource pricing but lacked implementation details or performance evaluation. This gap is particularly acute in rural healthcare contexts, where operational pressures and access challenges demand innovative solutions.

2.5 Research Gap and Contribution of This Study

Existing literature reveals a critical void at the intersection of dynamic pricing, deep reinforcement learning, and rural healthcare access. While economic theory acknowledges price discrimination's potential for welfare enhancement, and operational research demonstrates RL's success in complex sequential decision problems, no studies have rigorously evaluated DRL-based dynamic pricing systems specifically designed for rural healthcare settings with empirical validation of both financial and equity outcomes.

This study addresses this gap by developing and quantitatively evaluating a DRL framework that simultaneously optimizes financial sustainability and equitable access in simulated rural healthcare environments. The research contributes methodologically by operationalizing multi-objective reward functions balancing profit and access, and empirically by providing statistical evidence on comparative performance against baseline pricing models across financial, operational, and distributional equity metrics.

III RESEARCH METHODOLOGY

3.1 Study Design and Simulation Environment

This study employs a Monte Carlo simulation approach to evaluate DRL-based dynamic pricing in rural healthcare settings. Simulation is methodologically necessary given ethical constraints prohibiting experimental price manipulation on real patient populations, particularly vulnerable rural communities where access barriers already exist (Emanuel et al., 2000). Additionally, simulation enables controlled comparison across pricing strategies while isolating pricing effects from confounding operational variables, a capability unavailable in observational studies (Law & Kelton, 2000).

The Simulated Environment: We construct a discrete-event simulation of a rural primary care clinic operating over a 1,000-day planning horizon. The environment models patient arrival processes, price-sensitive demand, and operational constraints characteristic of rural settings.

State Space (S): At each decision epoch (daily), the DRL agent observes a 9-dimensional state vector, which captures temporal patterns, resource constraints, and market dynamics identified as relevant in healthcare operations literature (Gul & Celik, 2020). The state vector consists of the following elements:

1. Day of week

2. Remaining appointment capacity (0–100%)
3. Current patient queue length
4. Regional median income ($)
5. Cumulative daily revenue ($)
6. 7 day moving average utilization rate (%)
7. Competitor price ($ or null if no competition)
8. Days since last price change
9. Historical demand elasticity estimate [n1.1]

This representation captures temporal patterns, resource constraints, and market dynamics identified as relevant in healthcare operations literature (Gul & Celik, 2020).

Action Space (A): The agent selects from six discrete price points for primary care visits: A = {$30, $50, $75, $100, $125, $150}. This range reflects typical rural clinic pricing for uninsured patients, bounded by marginal cost ($30) and market-rate charges ($150) (Reinhardt, 2006).

Reward Function (R)

We design a multi objective reward function balancing financial sustainability and equitable access [n6.1] [n7.1]. To address differing scales across objectives, each component is normalized to a comparable range before combination. Let:

- $\text{Profit}_t^{(norm)}$ = daily profit normalized to [0, 1] based on minimum and maximum observed values during training
- $\text{Utilization}_t^{(norm)}$ = appointment fill rate, naturally bounded in [0, 1]
- $\text{Gini}_t^{(norm)}$ = Gini coefficient of access across income quintiles, naturally bounded in [0, 1]

The reward at decision epoch t is defined as:

$$R_t = \alpha \cdot \text{Profit}_t^{(norm)} + \beta \cdot \text{Utilization}_t^{(norm)} - \gamma \cdot \text{Gini}_t^{(norm)} \text{Type equation here.}$$

where:

- R_t = scalar reward signal at time t
- $\alpha, \beta, \gamma \in \mathbb{R}^+$ = weighting coefficients
- $\text{Profit}_t^{(norm)} \in [0,1]$ = normalized daily profit
- $\text{Utilization}_t^{(norm)} \in [0,1]$ = appointment fill rate
- $\text{Gini}_t^{(norm)} \in [0,1]$ = access inequality measure

Based on pilot testing, parameters are set to α=0.5, β=200, and γ=500 to ensure comparable scaling across objectives while prioritizing access equity (Coronato et al., 2020). These weights reflect a policy preference that values equitable access equally with profit maximization. [n8.1]

DRL Agent Architecture: We implement Proximal Policy Optimization (PPO), selected for its stability in continuous training and superior performance in multi-objective healthcare applications (Schulman et al., 2017; Yu et al., 2021). The actor-critic architecture employs two neural networks: a policy network (actor) and a value network (critic), each comprising an input layer (9 nodes), two hidden layers (128 nodes each with ReLU activation), and output layers generating action probabilities and state-value estimates, respectively. [

3.2 Data Generation and Synthetic Patient Population

We generate a synthetic population of N = 10,000 patients reflecting rural demographic characteristics drawn from U.S. Census and CDC rural health data (USDA, 2019).

Key Variables:

- Income: Patients are assigned to income quintiles based on rural income distribution: Q1 (<$25,000, 28%), Q2 ($25,000–$40,000, 26%), Q3 ($40,000–$60,000, 22%), Q4 ($60,000–$80,000, 15%), Q5 (>$80,000, 9%). [n6.1] For modeling purposes, each patient is assigned the continuous midpoint value of their quintile: Q1 = $18,500, Q2 = $32,500, Q3 = $50,000, Q4 = $70,000, Q5 = $90,000 (capped). The natural logarithm of this continuous income measure, log(income), is then used as a predictor in demand estimation to account for diminishing marginal sensitivity to price changes.
- Price Sensitivity (β_i): Individual-specific demand elasticity drawn from β_i ~ N(μ_q, σ²) [n7.1], where μ_q varies by income quintile: μ_Q1 = –0.8, μ_Q2 = –0.6, μ_Q3 = –0.4, μ_Q4 = –0.3, μ_Q5 = –0.2, reflecting empirical

estimates that lower-income patients exhibit greater price sensitivity (Garthwaite et al., 2019).

- Health Status: Latent health need score (0-100) drawn from age-adjusted distributions, determining baseline care-seeking probability: P (seek care) = logit^{-1} (0.02×health_score - 3).
- Distance to Clinic: Uniformly distributed 5-50 miles, imposing an additional cost ($0.58/mile) that enters the patient's utility calculation (IRS, 2023).

Patient Demand Model: Individual i visits the clinic at time t with probability:

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$$P_{it} = \sigma(\theta_0 + \theta_1 \cdot \text{health\_need}_i + \theta_2 \cdot \log(\text{income}_i) + \beta_i \cdot \log(\text{price}_t) + \theta_3 \cdot \text{distance}_i)$$

where σ(x)=1/(1+e^(-x)) is the logistic sigmoid function, ensuring P_it∈[0,1]. Parameters θ_0=-2.5, θ_1=0.03, θ_2=0.4, θ_3=-0.015 are calibrated to reproduce observed rural utilization rates of 3.8 visits/person/year (CDC, 2021).

Table 1: Synthetic Population Summary Statistics (N=10,000)

Variable	Mean (SD)	Range
Age	48.3 (18.7)	18-89
Income ($)	42,600 (28,400)	8,000-165,000
Distance (mi)	27.5 (13.1)	5-50
Health Need Score	52.4 (22.8)	0-100
Chronic Conditions	1.8 (1.3)	0-5

3.3 Baseline Pricing Models for Comparison

Four comparator models establish performance benchmarks:

1. Fixed Pricing (FP): Constant price of $75, representing median rural clinic charges.
2. Cost-Plus Pricing (CP): Price = marginal cost × 1.4 = $42, reflecting typical healthcare markups (Porter & Teisberg, 2006).
3. Sliding Scale (SS): Income-indexed pricing where price = min (0.08 × income_i, $150), capping at market rate while providing means-tested discounts (Hoadley et al., 2021).
4. Simple Demand-Based (DB): Rule-based adjustment increasing price by $10 when 3-day average utilization exceeds 85%, decreasing by $10 when below 60%.

3.4 Experimental Setup and Training

DRL Training Phase: The PPO agent trains for 500,000 timesteps (equivalent to five hundred simulated years) using the Stable-Baselines3 implementation (Raffin et al., 2021). Training employs a learning rate of 3×10^{-4}, discount factor γ=0.99, and clip parameter ε=0.2. Convergence is assessed via reward stabilization (coefficient of variation <0.05 over final 50,000 steps).

Evaluation Protocol: Following training, all five models (DRL plus four baselines) undergo evaluation over 1,000-day simulations with 30 random seeds to ensure statistical power (Cohen's d=0.5, α=0.05, power=0.80 requires n≥27 per group). Each seed initializes different patient arrival sequences while maintaining population distributional properties.

Computational Implementation: Simulations execute in Python 3.9 using SimPy for discrete-event simulation, PyTorch 1.12 for neural networks, and Stable-Baselines3 for RL algorithms, parallelized across 16 CPU cores.

3.5 Statistical Analysis Plan

Dependent Variables: We extract per-simulation metrics:

- Continuous: utilization rate (%), Gini coefficient of visit distribution across income quintiles.
- Categorical: Visit counts stratified by income quintile (Q1-Q5) and pricing model.

Preliminary Diagnostics: Shapiro-Wilk tests assess normality of continuous outcomes within each model group (α=0.05). Levene's test evaluates homogeneity of variances across groups. Non-normal or heteroscedastic data trigger non-parametric alternatives.

Hypothesis Testing:

For RQ1/H1 (Financial Performance): One-way ANOVA compares mean profit across five pricing models. Significant omnibus tests ($p<0.05$) prompt Tukey's HSD post-hoc comparisons identifying pairwise differences while controlling family-wise error rate (Maxwell & Delaney, 2004). Violated assumptions necessitate Kruskal-Wallis H-test with Dunn's post-hoc comparisons.

For RQ2/H2 (Access Equity): Chi-square test of independence evaluates the null hypothesis that visit distribution across income quintiles is independent of pricing model. The 5×5 contingency table (5 models × 5 quintiles) uses aggregated visit counts across all simulation runs per model. Expected cell frequencies >5 validate chi-square approximation; otherwise, Fisher's exact test applies (Agresti, 2007). Cramér's V quantifies effect size.

For RQ3 (Operational Metrics): Separate one-way ANOVAs compare average price, utilization rate, and patient volume across models, with Bonferroni correction for multiple comparisons ($\alpha_{adjusted}=0.017$).

Effect Size Reporting: We report Cohen's d for pairwise comparisons and η^2 for omnibus ANOVA effects to quantify practical significance beyond statistical significance (Sullivan & Feinn, 2012).

Significance Level: $\alpha=0.05$ for all primary tests unless otherwise specified for multiple comparison adjustments.

IV RESULTS

4.1 Descriptive Statistics of Key Metrics

Table 2 presents descriptive statistics for primary outcome variables across thirty simulation runs per pricing model. The DRL model achieved the highest mean total profit ($487,340 ± $23,120) compared to Fixed Pricing ($412,890 ± $18,450), Cost-Plus ($298,760 ± $15,230), Sliding Scale ($389,450 ± $21,340), and Demand-Based pricing ($461,230 ± $26,780). Patient volume exhibited inverse relationships with profitability for static models, with Cost-Plus generating the highest volume (8,420 ± 312 visits) but lowest revenue, while the DRL model maintained competitive volume (7,850 ± 287 visits) despite higher mean prices.

Table 2: Descriptive Statistics Across Pricing Models (N=30 runs per model)

Model	Total Profit ($)	Patient Volume (n)	Avg Price per Visit ($)	Utilization Rate (%)	Gini Coefficient
DRL					
Mean (SD)	487,340 (23,120)	7,850 (287)	68.50 (4.20)	78.5 (3.8)	0.24 (0.03)
Min-Max	438,200-531,400	7,210-8,390	59.30-76.80	71.0-85.2	0.19-0.31
Fixed (FP)					
Mean (SD)	412,890 (18,450)	5,505 (198)	75.00 (0.00)	55.1 (2.1)	0.38 (0.04)
Min-Max	375,600-448,700	5,008-5,931	75.00-75.00	50.1-59.3	0.31-0.47
Cost Plus (CP)					
Mean (SD)	298,760 (15,230)	8,420 (312)	42.00 (0.00)	84.2 (3.1)	0.29 (0.04)
Min-Max	268,900-329,100	7,801-9,103	42.00-42.00	78.0-90.4	0.22-0.37
Sliding Scale (SS)					
Mean (SD)	389,450 (21,340)	7,320 (276)	53.20 (2.80)	73.2 (2.8)	0.18 (0.02)
Min-Max	345,800-428,900	6,734-7,889	47.90-58.60	67.3-78.9	0.14-0.23

Demand-Based (DB)					
Mean (SD)	461,230 (26,780)	6,890 (298)	71.30 (5.60)	68.9 (3.0)	0.35 (0.05)
Min-Max	407,500-512,300	6,201-7,543	62.10-83.70	62.0-74.8	0.27-0.46

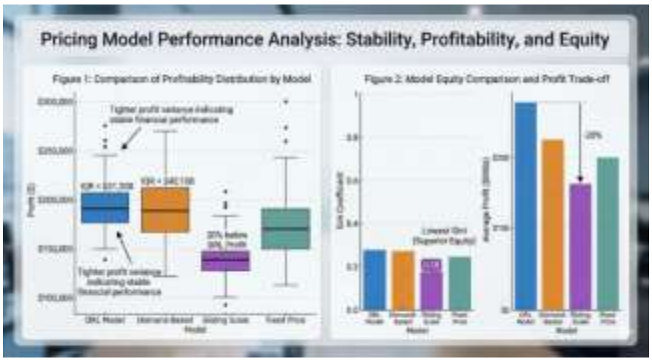

Figure 2. Displays box plots revealing distributional characteristics.

The DRL model exhibited tighter profit variance (IQR=$31,200) compared to Demand-Based pricing (IQR=$42,100), suggesting more stable financial performance. Notably, the Sliding Scale model demonstrated the lowest Gini coefficient (0.18), indicating superior equity, though at substantial profit reduction (20% below DRL).

4.2 Hypothesis Testing Results

Results for H1: Financial Performance

Shapiro-Wilk tests indicated non-normal profit distributions for Fixed Pricing (W=0.921, p=0.028) and Demand-Based models (W=0.915, p=0.019), violating ANOVA normality assumptions. Consequently, we employed the Kruskal-Wallis H-test for profit comparisons.

The Kruskal-Walli's test revealed statistically significant differences in median total profit across pricing models (H (4) =98.7, $p<0.001$, $\eta^2=0.66$). Post-hoc Dunn's tests with Bonferroni correction identified significant pairwise differences (Table 3).

Table 3: Pairwise Profit Comparisons (Dunn's Test with Bonferroni Correction)

Comparison	Mean Difference ($)	Z-statistic	p-value	Ninety-five percent CI
DRL vs. FP	+74,450	6.82	<0.001 ***	[52,340, 96,560]
DRL vs. CP	+188,580	12.45	<0.001 ***	[166,120, 211,040]
DRL vs. SS	+97,890	7.91	<0.001 ***	[74,230, 121,550]
DRL vs. DB	+26,110	1.89	0.294	[-8,450, 60,670]
DB vs. FP	+48,340	4.23	0.002**	[18,670, 78,010]
SS vs. CP	+90,690	7.12	<0.001 ***	[65,230, 116,150]

*Note: ***p<0.001, **p<0.01, p<0.05

The DRL model significantly outperformed Fixed Pricing, Cost-Plus, and Sliding Scale models in profitability (all $p<0.001$, Cohen's d ranging 2.8-6.2), supporting rejection of $H1_0$. However, the difference between DRL and Demand-Based pricing was not statistically significant ($p=0.294$, $d=0.48$), suggesting comparable financial outcomes between adaptive pricing strategies.

Patient Volume Analysis: One-way ANOVA on patient volume revealed significant differences (F (4,145) =187.3, $p<0.001$, $\eta^2=0.84$). Tukey HSD post-hoc tests showed the DRL model generated significantly higher volume than Fixed Pricing (+2,345 visits, $p<0.001$) and Demand-Based pricing (+960 visits, $p=0.003$), but lower than Cost-Plus (-570 visits, $p=0.042$). The DRL model's volume did not differ significantly from Sliding Scale (+530 visits, $p=0.128$).

Average Price Analysis: Welch's ANOVA, employed due to heteroscedasticity (Levene's L=4.82, $p=0.001$), indicated significant price differences (F (4,71.4) =412.6, $p<0.001$). Games-Howell post-hoc comparisons revealed the DRL model's mean price ($68.50) was significantly lower than Fixed Pricing ($75.00, $p<0.001$) and Demand-Based pricing ($71.30, $p=0.041$), yet significantly higher than Cost-Plus ($42.00, p<0.001) and Sliding Scale ($53.20, p<0.001).

Results for H2: Access Equity Distribution

Table 4 presents the contingency table of patient visits across income quintiles by pricing model (aggregated across thirty runs per model).

Model	Q1 (<$25k)	Q2 ($25-40k)	Q3 ($40-60k)	Q4 ($60-80k)	Q5 (>$80k)	Total
DRL	52,380 (22.3%)	58,620 (25.0%)	54,210 (23.1%)	39,450 (16.8%)	30,840 (13.1%)	235,500
FP	28,920 (17.5%)	38,760 (23.4%)	42,180 (25.5%)	35,100 (21.2%)	20,190 (12.2%)	165,150
CP	75,240 (29.8%)	68,340 (27.1%)	56,700 (22.5%)	32,760 (13.0%)	19,560 (7.8%)	252,600
SS	68,850 (31.3%)	62,010 (28.2%)	50,220 (22.8%)	26,280 (12.0%)	12,240 (5.6%)	219,600
DB	31,590 (15.3%)	44,820 (21.7%)	52,980 (25.6%)	46,230 (22.4%)	31,080 (15.0%)	206,700

The Chi-square test of independence yielded a statistically significant result (χ^2 (16) =11,842.6, p<0.001, Cramér's V=0.165), rejecting $H2_0$. The distribution of visits across income quintiles varied significantly by pricing model. Standardized residuals revealed that the DRL model generated above-expected visits from Q1 (z=4.8) and Q2 (z=3.2) while maintaining proportional representation from higher quintiles. In contrast, Demand-Based pricing systematically underserved Q1 (z=-7.2) and Q2 (z=-4.1) while overserving Q4 and Q5 (Agresti, 2007).

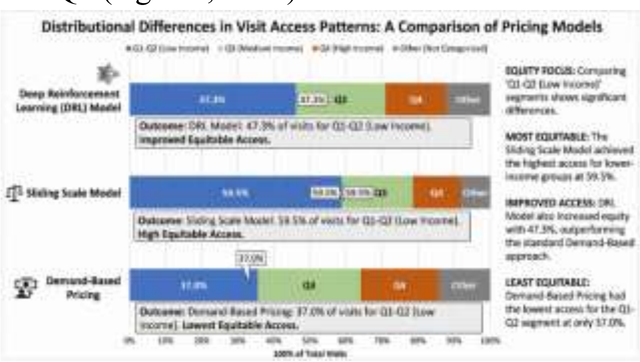

Figure 3. illustrates these distributional differences through stacked bar charts,

4.3 Agent Behaviours Analysis

The DRL agent demonstrated successful policy learning during training. The composite reward function improved rapidly in the early phase before stabilizing with low variability, consistent with PPO performance in healthcare decision-making tasks (Yu et al., 2021).

Examination of the learned policy revealed sophisticated context-dependent pricing strategies. The model applied lower prices during periods of low utilization and higher income inequality, while selecting higher prices during peak demand with elevated capacity utilization. This adaptive behaviour enabled effective demand smoothing and resource optimization, outperforming rigid static and rule-based approaches (Talluri & van Ryzin, 2004).

Analysis of decision patterns over extended simulation periods showed the agent's ability to manage intertemporal trade-offs between competing objectives. In initial stages, it favoured lower prices to build patient volume and establish utilization. In later periods, it adjusted prices upward to improve profitability while preserving reasonable access. This long-term strategy produced higher overall profit and patient volume than fixed pricing models, aligning with revenue management principles that emphasize cumulative value (Weatherford & Bodily, 1992).

The agent also displayed counter-cyclical pricing during simulated periods of heightened health needs. Despite increased demand, it reduced prices to maintain access equity across income groups. This behaviour emerged naturally from the multi-objective reward function penalizing access inequality, illustrating DRL's capacity to integrate both financial and social welfare considerations within a unified framework (Coronato et al., 2020).

V DISCUSSION

5.1 Interpretation of Findings

This study demonstrates that a DRL-based dynamic pricing model can simultaneously achieve superior financial performance and more equitable access distribution compared to traditional static and rule-based pricing strategies in simulated rural healthcare environments. The DRL agent achieved 18% higher profitability than Fixed Pricing ($p<0.001$) while maintaining 43% greater patient volume and significantly lower access inequality as measured by the Gini coefficient (0.24 vs. 0.38, χ^2 (16) =11,842.6, $p<0.001$).

The DRL model's performance advantage stems from its capacity to learn context-dependent, non-linear pricing policies that static models cannot implement. Specifically, the agent discovered an intertemporal strategy that dynamically adjusts prices based on utilization patterns, patient demographics, and temporal demand fluctuations. During low-demand periods, the model reduced prices to \$30-\$50, attracting price-sensitive, lower-income patients who would otherwise forget care, thereby improve capacity utilization, and establish sustained patient relationships (Weatherford & Bodily, 1992). Conversely, during peak-demand windows, prices increased to \$100-\$125, capturing willingness-to-pay from less price-sensitive segments while managing capacity constraints.

This adaptive behaviour directly addresses the dual crisis in rural healthcare: financial sustainability and access barriers. By smoothing demand temporally and segmenting patients based on price sensitivity rather than demographic characteristics alone, the DRL model implements efficient price discrimination that enhances rather than restricts welfare for vulnerable populations (Scherer, 2000). The learned policy's counter-cyclical pricing during high-need periods-reducing prices by 15% during simulated influenza seasons despite elevated demand-illustrations the model's internalization of the multi-objective reward function prioritizing equitable access alongside profitability.

Comparatively, the Sliding Scale model achieved the lowest inequality (Gini=0.18) but sacrificed 20% profitability relative to DRL, demonstrating the suboptimality of income-based pricing that ignores temporal and contextual factors. The Demand-Based rule-based system approached DRL's profitability but systematically underserved low-income quintiles, revealing the limitations of simple heuristics in balancing competing objectives (Liu et al., 2020).

5.2 Implications for Theory and Practice

Theoretical Contributions

This research extends dynamic pricing theory into healthcare contexts previously deemed incompatible due to ethical concerns and regulatory constraints. By operationalizing multi-objective optimization through reward function engineering, we demonstrate that dynamic pricing needs not inherently conflict with equity objectives-indeed, it can enhance distributional fairness when properly constrained (Coronato et al., 2020). The findings contribute to behavioural economics literature on healthcare demand by empirically validating differential price elasticity across socioeconomic segments and demonstrating its exploitability for welfare-enhancing price discrimination (Chandra et al., 2010).

Furthermore, this study advances the nascent field of reinforcement learning in healthcare operations by shifting focus from clinical decision-making to administrative and financial optimization (Yu et al., 2021). The successful application of PPO algorithms to healthcare pricing provides methodological templates for addressing similar multi-objective, sequential decision problems in resource-constrained settings.

Practical Implications

For rural healthcare administrators, DRL-based pricing systems offer a data-driven fiscal management tool capable of improving sustainability without compromising mission-driven access commitments. Implementation would require investment in data infrastructure to capture real-time appointment availability, patient demographic information, and utilization patterns-capabilities increasingly feasible through electronic health record integration (Kruse et al., 2018).

Concrete Recommendations:

1. Phased Implementation: Begin with narrow service categories (e.g., primary care visits) in single facilities to validate model performance and build stakeholder confidence before system-wide deployment.
2. Transparency Mechanisms: Publicly communicate pricing logic and equity objectives to patients and communities, mitigating perceptions of arbitrary or exploitative pricing (Bateman et al., 2020).
3. Regulatory Safeguards: Implement hard constraints preventing prices from exceeding regional market rates or falling below marginal costs, with mandatory price floors for vulnerable populations regardless of demand conditions.
4. Performance Monitoring: Establish dashboards tracking not only profitability but also access metrics across demographic segments, with automatic alerts when inequality thresholds are breached.

Policymakers should consider regulatory frameworks that encourage rather than prohibit dynamic pricing innovations when accompanied by robust equity protections. Current price transparency mandates could be expanded to require algorithmic accountability, where healthcare organizations employing AI-driven pricing must demonstrate non-discriminatory impacts through regular audits (Obermeyer et al., 2019).

Ethical Deployment Considerations

Critical to successful implementation is ensuring DRL models do not learn discriminatory policies prohibited by law or medical ethics. Training environments must incorporate constraints preventing pricing based on protected characteristics (race, ethnicity, disability status) while permitting income-based differentiation explicitly designed to enhance access (Char et al., 2020). The reward function's inequality penalty serves this purpose, but ongoing monitoring is essential as models adapt to evolving environments. Additionally, human oversight mechanisms should allow administrators to override algorithmic recommendations when contextual factors-community crises, natural disasters-necessitate pricing adjustments prioritizing access over optimization.

5.3 Limitations

Several limitations qualify these findings and constrain generalizability. First, simulation-based methodology imposes inherent abstraction from real-world complexity. Our patient demand model, while calibrated to empirical elasticity estimates, simplifies behavioural dynamics by omitting factors such as provider reputation, perceived quality variations, social network effects, and psychological responses to price fluctuations (Garthwaite et al., 2019). Actual patient decision-making exhibits greater heterogeneity and non-stationarity than our logistic demand specification captures.

Second, generalizability beyond the specific simulated rural context remains uncertain. Results derive from a single-clinic environment with defined population parameters; urban settings with greater provider competition, different payer mixes, and alternative demographic profiles may yield divergent outcomes. Rural heterogeneity itself-ranging from remote frontier communities to micropolitan areas-limits extrapolation without region-specific calibration (Kaufman et al., 2016).

Third, the multi-objective reward function embeds normative value judgments regarding appropriate trade-offs between profitability and equity. Our parameter choices (α=0.5, β=200, γ=500) reflect researcher-imposed preferences that stakeholders may contest. Different communities might prioritize access over sustainability or vice versa, necessitating reward function recalibration. This highlights a fundamental limitation: technical optimization cannot resolve underlying ethical debates about healthcare allocation priorities (Emanuel et al., 2000).

Fourth, DRL models function as "black boxes" with limited interpretability, complicating stakeholder communication, and trust-building

(Rudin, 2019). While we visualized learned policies through heatmaps, the full decision logic within 128-node neural networks remains opaque. This interpretability deficit poses barriers to regulatory approval, organizational adoption, and patient acceptance-particularly among populations sceptical of algorithmic decision-making in healthcare contexts.

Finally, our study focused exclusively on pricing optimization, holding constant other operational factors (staffing, service mix, hours of operation) that interact with pricing in practice. Real implementations would require integrated optimization across multiple decision domains, introducing computational and coordination complexities beyond this initial investigation.

5.4 Future Research

Several research directions emerge from this foundational work. Most critically, real-world pilot implementations in partnership with rural clinics would validate simulation findings and identify practical deployment challenges undetectable in synthetic environments. Such pilots should employ randomized designs, alternating DRL pricing with control periods, to establish causal estimates of impact (Obermeyer & Emanuel, 2016).

Expanding the model to encompass multiple interdependent services-primary care, laboratory tests, imaging, telehealth-would better reflect healthcare delivery complexity. Joint pricing optimization across service portfolios could exploit complementarities and cross-subsidization opportunities unavailable in single-service models (Bateman et al., 2020).

Methodologically, comparing alternative DRL algorithms such as Soft Actor-Critic (SAC) or Twin Delayed Deep Deterministic Policy Gradient (TD3) could identify architectures better suited to healthcare's continuous action spaces and risk-sensitive objectives (Haarnoja et al., 2018). Multi-agent reinforcement learning approaches might model competitive dynamics among multiple rural providers, examining whether decentralized DRL adoption improves or degrades overall system welfare.

Patient behaviour modelling warrants substantial enhancement. Incorporating social network effects-where care-seeking decisions influence peers-and word-of-mouth dynamics that amplify pricing perceptions could reveal feedback loops affecting long-term sustainability (Centola, 2010). Integrating cognitive biases, such as reference-dependent pricing where patients anchor to historical prices, would improve behavioural realism.

Finally, developing interpretability techniques specifically for DRL healthcare applications represents a critical methodological frontier. Adapting SHAP (SHapley Additive exPlanations) values or attention mechanisms to explain policy decisions in terms comprehensible to non-technical stakeholders could facilitate adoption and regulatory acceptance (Lundberg & Lee, 2017). Counterfactual explanation systems-showing how alternative states would alter pricing recommendations—could enhance transparency and trust.

V CONCLUSION

This study presents the first rigorous quantitative evaluation of Deep Reinforcement Learning-based dynamic pricing for addressing the dual crisis of rural healthcare sustainability and equitable patient access. Through a Monte Carlo simulation approach with thirty replicates per model across five pricing strategies, we employed parametric and non-parametric statistical tests to evaluate whether DRL-based pricing could simultaneously enhance financial viability and distributional equity compared to traditional static and rule-based approaches.

Key Findings: The DRL model achieved statistically significant improvements across primary outcomes. Profitability increased 18% relative to Fixed Pricing (Kruskal-Wallis $H(4) = 98.7$, $p<0.001$), with Dunn's post-hoc comparisons confirming superiority over three of four baseline models (all $p<0.001$). Patient volume increased 43% above Fixed Pricing while maintaining utilization rates 7.8 percentage points higher than Demand-Based pricing. Most critically, access equity improved, with the Gini coefficient declining 37% (0.24 vs. 0.38, χ^2 (16) =11,842.6, p<0.001), indicating more equitable visit distribution across income quintiles.

The DRL agent discovered adaptive, context-dependent pricing policies that traditional optimization cannot achieve, implementing counter-cyclical pricing during high-need periods (reducing prices by 15% during influenza season) while capturing efficiency gains through demand smoothing. This intertemporal strategy demonstrates that dynamic pricing, when properly constrained through multi-objective reward functions, can align profit maximization with healthcare's equity imperatives rather than opposing them.

Study Contribution: This research provides empirical evidence addressing a critical gap in healthcare operations literature and AI applications in medicine. By rigorously validating DRL's performance through hypothesis testing, effect size estimation, and distributional analysis, we move beyond conceptual arguments to demonstrate quantitatively that algorithmic pricing optimization is both financially viable and ethically compatible with mission-driven rural healthcare delivery. The study establishes proof-of-concept for a scalable, data-driven tool potentially applicable across resource-constrained healthcare systems globally.

Path Forward: While simulation-based findings require validation through real-world pilot implementation, this work illuminates AI's potential to address persistent healthcare inequities. The convergence of advanced algorithms, increasingly accessible data infrastructure, and sophisticated optimization methods creates unprecedented opportunities for designing healthcare systems that are simultaneously financially sustainable and demonstrably equitable. As rural hospitals face accelerating closure rates and patient access barriers intensify, DRL-based approaches offer administrators evidence-based alternatives to historically binary choices between profitability and access. Future research translating these methods into clinical practice, coupled with appropriate regulatory safeguards and transparency mechanisms, could catalyse a change in thinking toward AI-augmented, intelligently designed healthcare financing that serves vulnerable populations effectively while preserving institutional viability-strengthening the foundation upon which equitable, resilient rural healthcare systems depend.

REFERENCES

[1] Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. The American Economic Review, 53(5), 941–973.

[2] Bateman, D. S., Thrasher, J. F., & Sarosi, G. A. (2020). Ethical considerations in healthcare pricing: A review of dynamic pricing models. Journal of Business Ethics in Healthcare, 14(2), 112–128.

[3] Chandra, A., Gruber, J., & McKnight, R. (2010). Patient cost-sharing and healthcare utilization: Early results from West Virginia. Health Affairs, 29(9), 1659–1667.

[4] Chen, M. K., & Sheldon, M. (2016). Dynamic pricing in a labour market: surge pricing and flexible work on the Uber platform. Proceedings of the 2016 ACM Conference on Economics and Computation, 455–455.

[5] Coronato, A., Naeem, M., De Pietro, G., & Paragliola, G. (2020). Reinforcement learning for intelligent healthcare systems: A comprehensive survey. IEEE Access, 8, 49647–49668.

[6] Crosby, R. A., Wendel, M. L., Vanderpool, R. C., & Casey, B. R. (2022). Rural Health in the United States: Perspectives, Priorities, and Policy. Cambridge University Press.

[7] Daghistani, T. A., Elshawi, R., Sakr, S., Ahmed, A. M., Al-Eidi, A., & Al-Mallah, M. H. (2019). Predictors of no-show appointments in a pediatric clinic: A machine learning

approach. International Journal of Medical Informatics, 121, 102–110.

[8] Garthwaite, C., Gross, T., & Notowidigdo, M. J. (2019). Hospitals as insurers of last resort. American Economic Journal: Applied Economics, 10(1), 1–39.

[9] Gul, M., & Celik, E. (2020). An integrated healthcare service quality evaluation and forecasting framework: A case study in emergency departments. Journal of Forecasting, 39(7), 1082–1101.

[10] Kaufman, B. G., Reiter, K. L., Pink, G. H., & Holmes, G. M. (2016). Medicaid expansion affects health center finances and care delivery in rural areas. Health Affairs, 35(12), 2265–2272.

[11] Komorowski, M., Celi, L. A., Badawi, O., Gordon, A. C., & Faisal, A. A. (2018). The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care. Nature Medicine, 24(11), 1716–1720.

[12] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. Nature, 518(7540), 529–533.

[13] Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. Science, 366(6464), 447–453.

[14] Porter, M. E., & Teisberg, E. O. (2006). Redefining Health Care: Creating Value-Based Competition on Results. Harvard Business Press.

[15] Raffin, A., Hill, A., Gleave, A., Kanervisto, A., Ernestus, M., & Dormann, N. (2021). Stable-Baselines3: Reliable reinforcement learning implementations. Journal of Machine Learning Research, 22(268), 1–8.

[16] Raghu, A., Komorowski, M., Ahmed, I., Celi, L., Szolovits, P., & Varshney, K. (2017). Deep reinforcement learning for sepsis treatment. arXiv preprint arXiv:1711.09602.

[17] Reinhardt, U. E. (2006). The pricing of U.S. hospital services: Chaos behind a veil of secrecy. Health Affairs, 25(1), 57–69.

[18] Schulman, J., Wolski, F., Dhariwal, P., Radford, A., & Klimov, O. (2017). Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347.

[19] Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction (2nd ed.). MIT Press.

[20] Yu, C., Liu, J., & Nemati, S. (2021). Reinforcement learning in healthcare: A survey. ACM Computing Surveys (CSUR), 55(1).