AIE424 : Intelligent Decision Support Systems

Personalized Antibiogram Optimization Using Linear Programming

This presentation introduces a linear programming framework designed to optimize antibiotic selection by integrating personalized antibiogram predictions. The system aims to maximize treatment efficacy while respecting clinical prescribing constraints, supporting antimicrobial stewardship goals. Simulations of 1,000 infections demonstrate improved coverage compared to clinician and random strategies. Budget-sweep analyses reveal thresholds for substituting broad-spectrum antibiotics with narrower alternatives, highlighting the potential to reduce resistance pressure in clinical practice.

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Introduction to Antimicrobial Resistance and Optimization

AMR Challenge

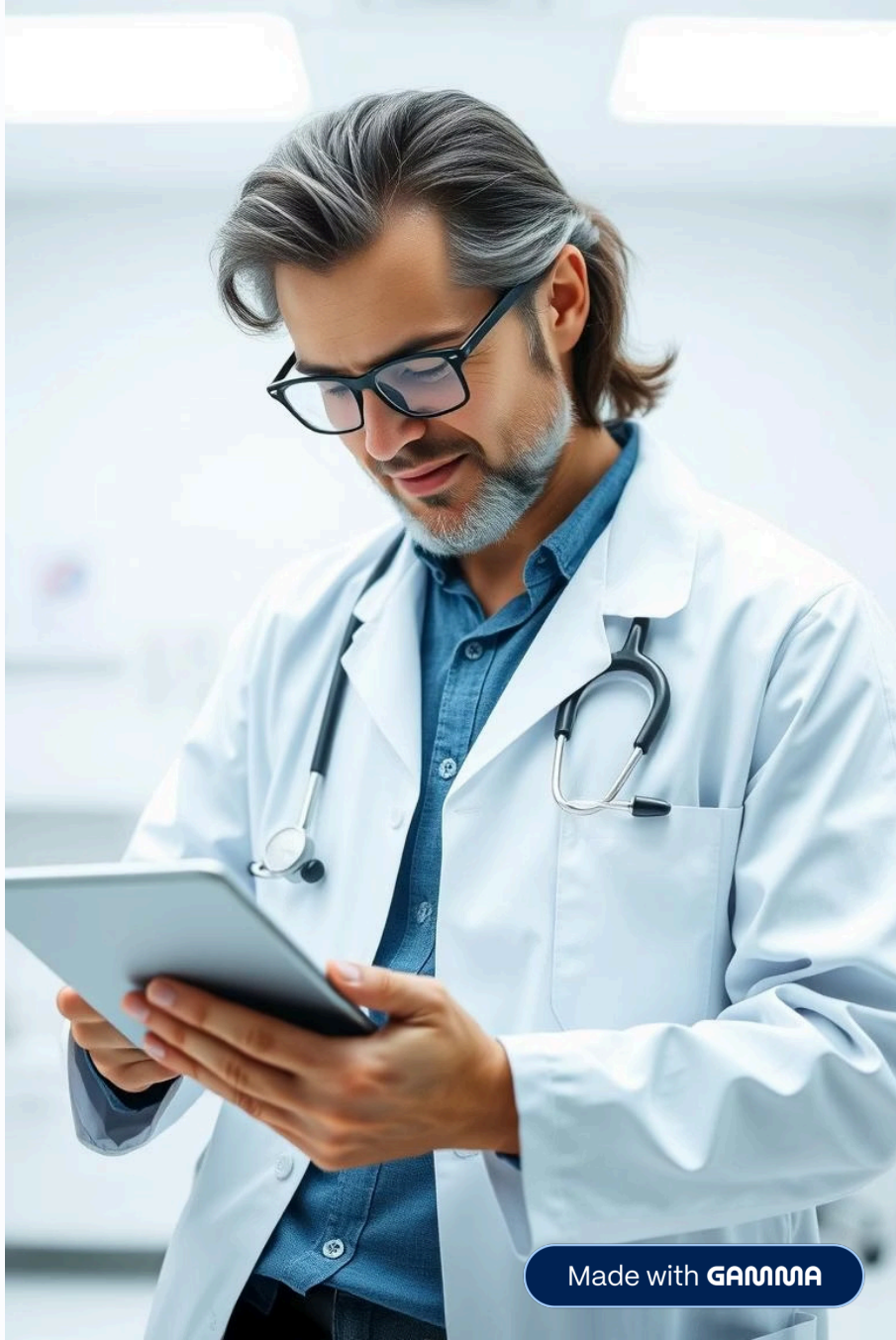
Antimicrobial resistance is a growing public health concern, worsened by overuse of broad-spectrum antibiotics in empiric therapy.

Optimization Goals

The framework maximizes treatment efficacy, minimizes broad-spectrum antibiotic use, and supports substitution with narrower agents under clinical constraints.

Simulation Approach

1,000 synthetic infections were simulated to compare random, clinician-guided, and optimized antibiotic allocations.



Methodology and Data Description

Data Description

Simulated dataset of 1,000 infections with true susceptibility and clinician and random antibiotic assignments across four drugs.

- Binary susceptibility indicators for Pip-Tazo, Cefepime, Ceftriaxone, Cefazolin
- Personalized antibiogram prediction probabilities with AUROC of 0.65

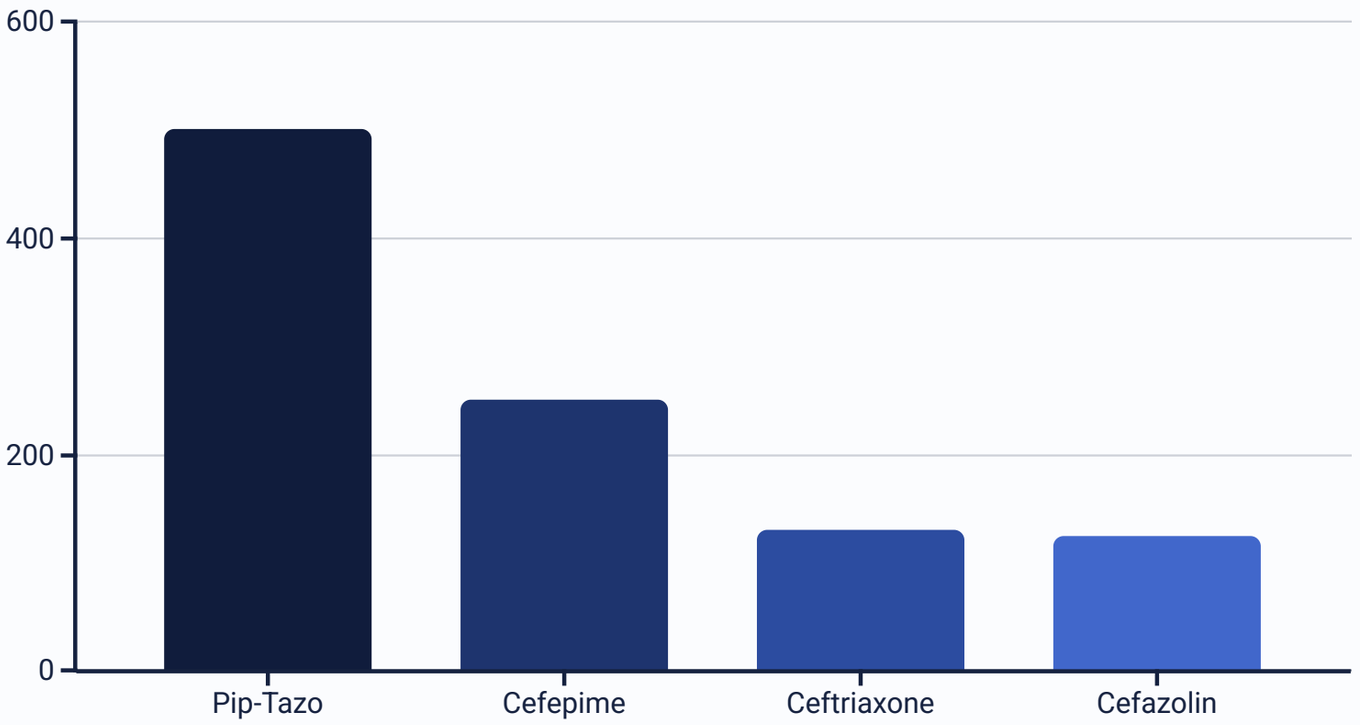
Linear Programming Model

Decision matrix assigns one antibiotic per infection, maximizing predicted susceptibility while respecting usage budgets.

- Single antibiotic per infection constraint
- Antibiotic usage budgets based on clinician patterns

Sample Data Snapshot

INFECTION_ID	Random_ABX_RX	Pip_Tazo	Cefepime	Ceftriaxone	Cefazolin	Pip_Tazo_predictions	Cefepime_predictions	Ceftriaxone_predictions	Cefazolin_predictions	ABX_RX
0	Pip_Tazo	1	1	1	1	0.571996	0.706604	0.648257	0.533554	Pip_Tazo
2	Pip_Tazo	1	1	0	1	0.760161	0.854547	0.172386	0.831246	Cefepime



Methodology: Linear Programming (LP)

Goal

Maximize total coverage across all infections and antibiotics.

Objective Function:

$$\underset{A}{\text{maximize}} \sum_{i=1}^{N} \sum_{j=1}^{K} \phi_{ij} a_{ij}$$

Constraints

Each infection must receive 1 antibiotic:

$$\sum_{j=1}^{K} a_{ij} = 1 \quad i = 1, \ldots, N$$

Antibiotic usage matches real-world totals:

$$\sum_{i=1}^{N} a_{ij} = c_j \quad j = 1, \ldots, K$$

Optimization Workflow and Evaluation Metrics

1 Baseline Solve

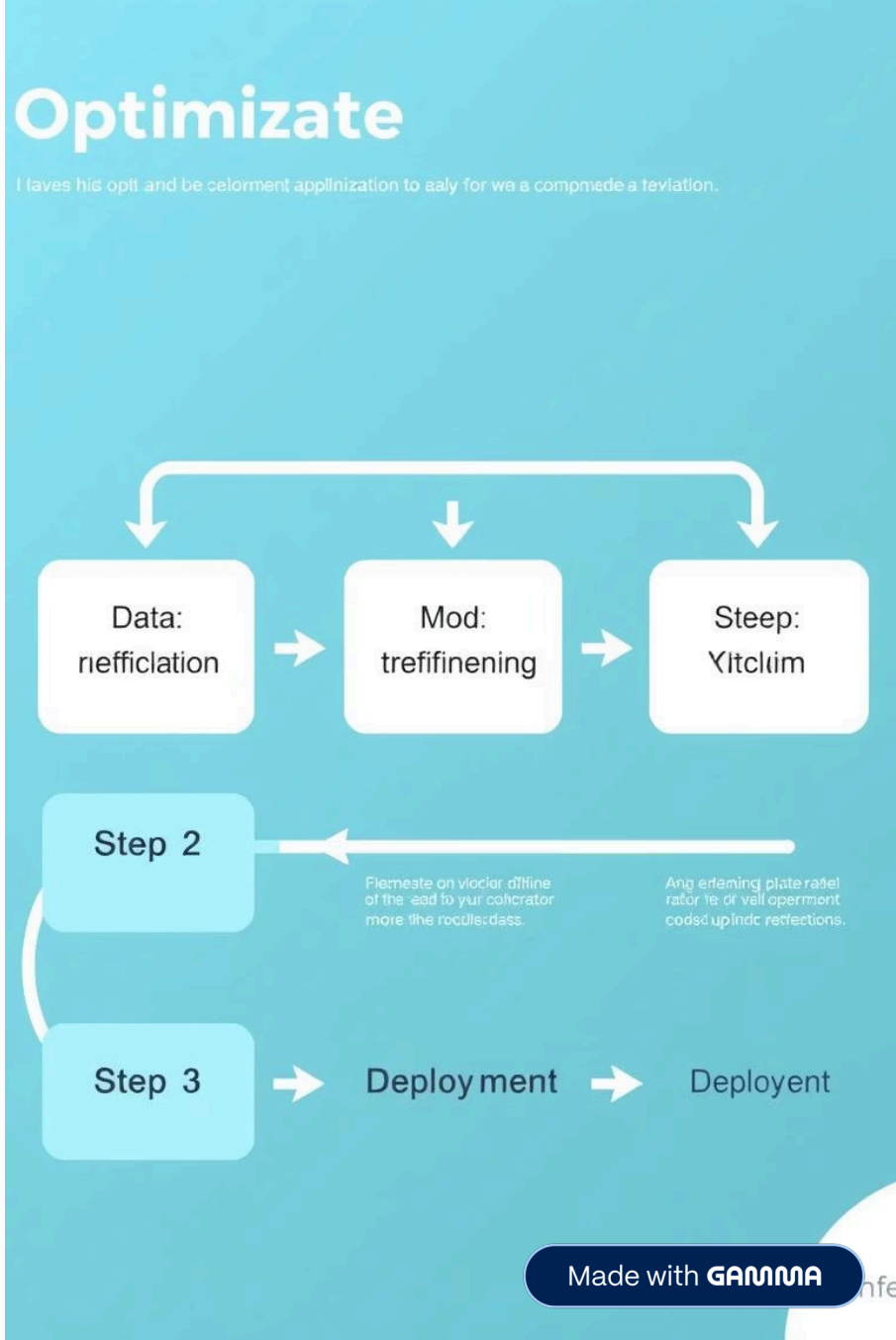
Optimize coverage using clinician-derived antibiotic budgets.

2 Budget Sweep

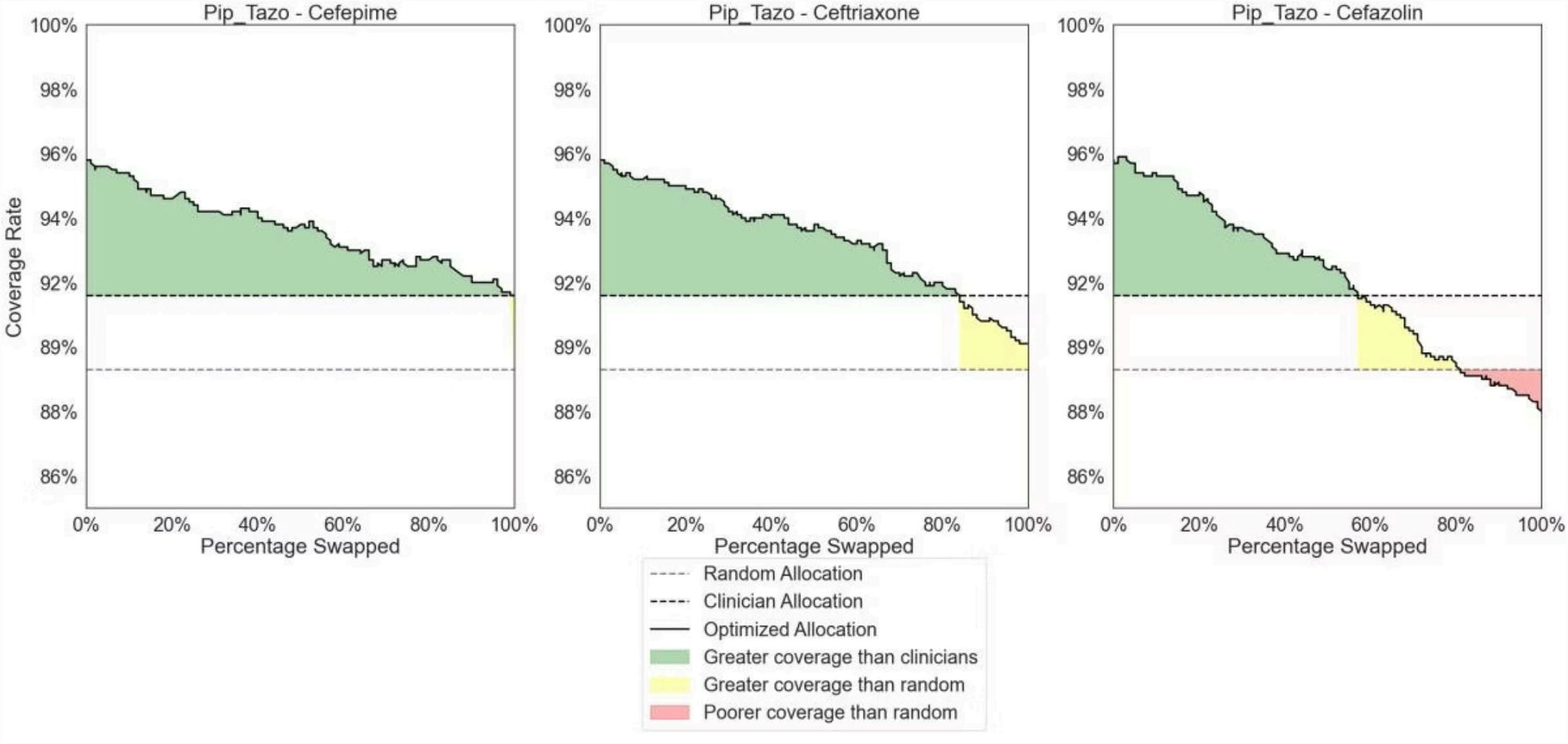
Incrementally substitute Piperacillin–Tazobactam with narrower-spectrum antibiotics and track coverage.

3 Evaluation Metrics

Coverage rate, AUROC for model discrimination, and average precision for probability reliability.



Results: Model Performance and Coverage Rates

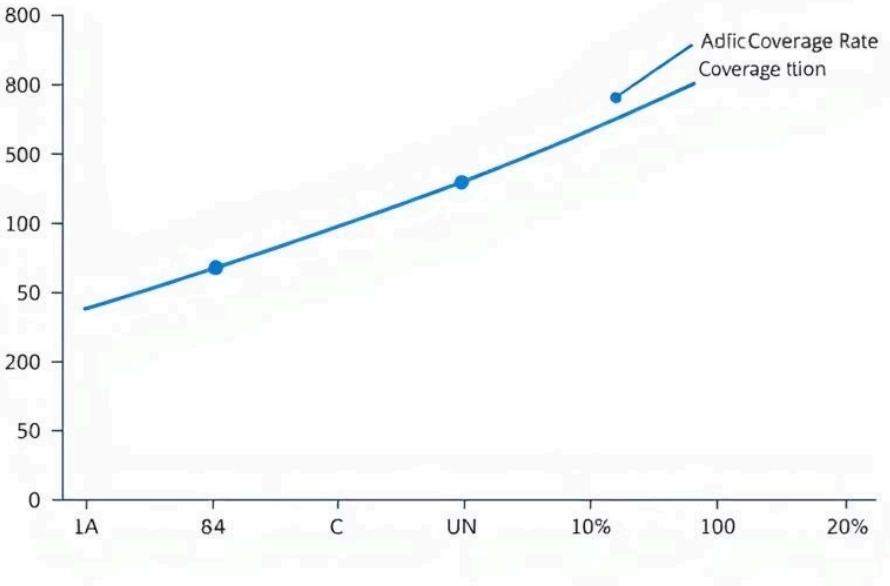


Model Performance

- AUROC ~0.65 across all four antibiotics
- High average precision indicating reliable predictions

Coverage Rates

- Random allocation: 89.3%
- Clinician allocation: 91.6%
- Optimized allocation: 95.8%



Budget Sweep Analysis: Substitution Thresholds

Pip-Tazo → Cefepime

Coverage stays above clinician benchmark up to 30% substitution and above 90% until 40%.

Pip-Tazo → Ceftriaxone

Coverage drops below clinician level at 20% substitution, limiting substitution potential.

Pip-Tazo → Cefazolin

Coverage falls below random allocation at 15% substitution, indicating early performance loss.

Discussion: Insights, Implications, and Limitations

Key Insights

LP optimization outperforms clinician and random prescribing by prioritizing high-likelihood treatments and reducing broad-spectrum use.

Substitution thresholds vary by antibiotic, with Cefepime allowing more flexibility.

Clinical Implications

- Supports targeted de-escalation policies for stewardship programs
- Potential integration with EHRs for real-time prescribing guidance

Limitations include synthetic data, omission of cost/resistance metrics, and single-drug assignment constraint.

Conclusion and Future Directions

Quantifiable Benefit

4.2% absolute coverage improvement over standard prescribing with LP optimization.

Stewardship Guidance

Defined substitution limits enable safer de-escalation of broad-spectrum antibiotics.

Future Work

Incorporate real-world data, multi-objective optimization, and adaptive budgeting for dynamic stewardship.

🙏 Thank You for Your Attention

We appreciate your time and interest in our work.

Let's work together towards more precise, responsible antibiotic use.

Engagement

Collaborate with clinical teams to improve antibiotic stewardship.

Innovation

Leverage data-driven models for personalized therapy decisions.

Impact

Enhance patient outcomes while minimizing resistance risks.