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AI-Powered Pharmacy Benefit Optimization: A Framework for Value-Based Care

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ABSTRACT
Pharmacy benefits accounts for a significant share of health care spending, and recent calls for a reduction in pharmacy benefit plans' administrative and drug acquisition costs have intensified interest in optimizing these benefits for all stakeholders. However, existing approaches mainly reduce spend without considering quality or access. Artificial intelligence opens new pathways for pharmacy benefit optimization that seek to improve cost, quality, and equity simultaneously. A conceptual framework is proposed that connects AI methods to multi-domain optimization goals through an integrated architecture of data, models, decision-making interfaces, and feedback loops. Potential value outcomes include reduced total cost of care, improved medication adherence and clinical endpoints, increased patient satisfaction, and strengthened equity; primary and secondary metrics are defined along with proposed data sources. A range of implementation considerations encompasses governance, regulation, ethics, change management, integration with existing workflows, and alignment with the priorities of pharmacy benefit managers and health systems.
Growing interest in the application of artificial intelligence (AI) technologies in health care is revolutionizing many aspects of clinical management. Unfortunately, pharmacy benefit managers (PBMs)—the companies that administer the pharmacy benefits of the majority of American health insurers—are facing increased scrutiny. The criticism centers on the perception that PBMs are collecting excessive administrative fees, increasing the spread between the pharmacy acquisition costs of drugs and the reimbursement paid by insurers, and lacking functional transparency. As a result, pharmacy benefits are being optimized mainly for cost reduction, rather than for simultaneous improvements in quality and equitable access. The integration of artificial intelligence into PMB operations represents an opportunity for more effective exploration of the tradeoffs among spending, quality, and accessibility.

Keywords: Pharmacy Benefit Optimization, Pharmacy Benefits Managers, Artificial Intelligence, Total Value-of-Care, Value-Based Healthcare .

1. INTRODUCTION

U.S. pharmacy benefits are usually optimized to minimize immediate costs while maximizing quality and access. Artificial intelligence can drastically enhance optimization by forecasting future costs and outcomes, employing an enhanced and broader set of possible changes to benefits, and reducing implementation costs. However, current research does not adequately define or explore AI-enabled pharmacy-benefit optimization. This gap is significant because pharmacy-benefit choices and structures affect the allocation and spending of about $1 trillion annually. Such choices are also becoming increasingly important for public-payer control of overall health care costs. Moreover, optimization from a total-cost-of-care perspective can help fulfill the promise of value-based health care for patients by addressing equity and by making participation attractive to providers across the continuum of care, not just acute-care specialists.

Pharmacy-benefit management companies (PBMs) currently evaluate a limited range of potential changes to pharmacy benefits. Proposed changes are selected more for feasibility than for value. Choices are often made based on short-term cost implications without regard to downstream effects on cost and quality across the broader health system. Correcting these deficiencies can require sizeable investments. Although the use of advanced analytic tools may allow traditional Pharmacy Benefit Management Company (PBM) processes to be performed faster and at a lower cost, the greater concentration on convening, scripting, and administering networks does not, by itself, create an advantage.

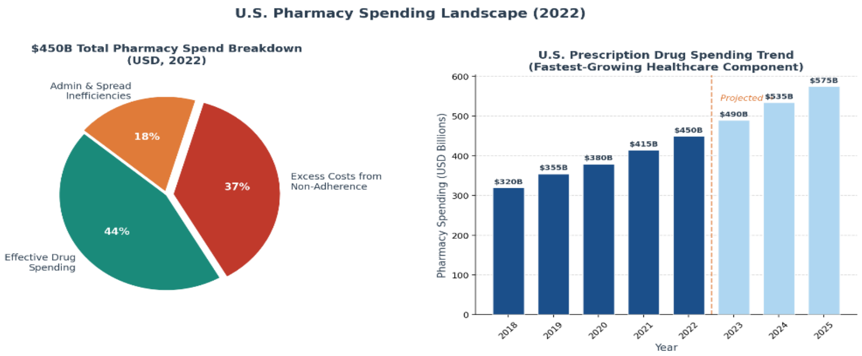
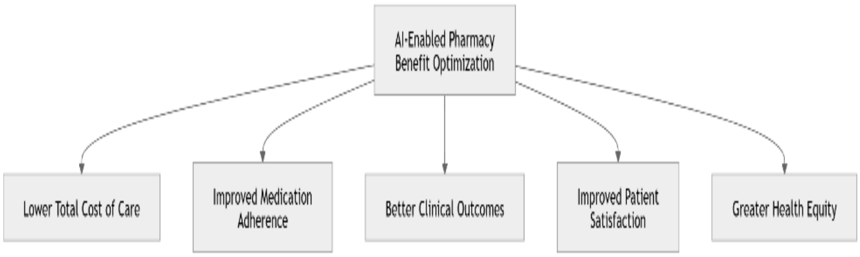


Fig: **U**.S. Pharmacy Spending Landscape – pie of the $450B breakdown + spending trend bar chart



Overall framework shows how the four core components (Data, AI Models, Decision Interfaces, and Feedback Loops) connect and feed into the four value outcome domains: Cost, Quality, Access, and Equity.

1.1.Background and Significance

Current pharmacy management (PM) models find it difficult to navigate the complex trade-offs among cost, quality, and access that optimize payments under value-based healthcare (VBHC). New approaches are needed in PBM design, governance, and processes that leverage artificial intelligence (AI) methods well established in other domains but rarely applied to PM. AI-enabled pharmacy benefit optimization in the context of VBHC-relevant patient-centric quality-of-care metrics guides new conceptions of pharmacy costs, clinical effectiveness, patient safety, and overall equity in distribution of healthcare resources.

The case for AI-driven pharmacy-benefit optimization starts with three arguments. First, numerous opportunities exist to reduce the total cost of care while simultaneously improving the quality of care for patients through better AI-enabled pharmacy management—in particular, enhanced predictive capabilities, optimization methods, and decision-support systems that facilitate both clinical and pharmacy management. Second, the current lack of such improvements has yielded considerable waste in healthcare spending. Third, the unique nature of pharmacy spending—both in terms of its cost burden and its frequent recognition as a key driver of poor health outcomes—suggests that the challenges of artificial-intelligence-enabled optimization of PM would greatly benefit from a solution-oriented approach capable of distilling these issues to a comprehensive and accessible form.

Table 1: Comparison of Traditional vs. AI-Powered Pharmacy Benefit Management

Feature	**Traditional PBM**	**AI-Powered PBM**
Formulary Management	Manual, periodic review	Continuous, data-driven optimization
Prior Authorization	Rule-based, manual review	Automated ML-based decisioning
Drug Utilization Review	Retrospective analysis	Real-time predictive analytics
Member Segmentation	Demographic-based	Behavioral + clinical risk stratification
Cost Prediction	Actuarial models	Deep learning forecasting
Fraud Detection	Claims auditing	Anomaly detection algorithms
Patient Adherence	Generic reminders	Personalized intervention engines
Outcomes Measurement	Claim-level metrics	Population health value metrics

2. Background and Rationale

In the US, prescription medication represents the fastest-growing component of healthcare spending, accounting for USD 450 billion in 2022—nearly 17% of total medical expenditure. Nevertheless, studies indicate high levels of medication nonadherence that compromise health and well-being, resulting in an estimated USD 250 billion in excess medical costs and leading to detrimental outcomes including increased hospitalization and mortality rates. In contemporary value-based healthcare (VBHC) models, pharmacy benefit maximization is a means of mitigating these issues within the pharmaceutical landscape and beyond. However, evidence suggests that existing pharmacy benefit managers (PBMs) continue to behave like middlemen rather than true partners in healthcare. By analyzing systemic shortcomings that inhibit PBMs' ability to fulfill this role, a case is made for the AI-enabled optimization of pharmacy benefits within a VBHC framework. Such optimization not only enhances patient care but also exerts positive effects on quality and cost—doing so, moreover, without requiring additional out-of-pocket costs from patients. Such a proposal can be synthesized in the following research statement: "Advancement of AI methods in PM represents a pivotal juncture in VBHC as it responds both to such models' imperatives and to emerging policies supporting health equity."

Table 2. Key AI/ML Techniques Used in Pharmacy Benefit Optimization

Technique	**Application Area**	**Example Use Case**
Natural Language Processing (NLP)	Clinical documentation	Extracting diagnoses from EHR notes
Random Forest / Gradient Boosting	Risk stratification	Predicting high-cost members
Reinforcement Learning	Formulary optimization	Dynamic drug tier adjustments
Deep Neural Networks	Drug interaction detection	Polypharmacy safety alerts
Clustering (K-Means, DBSCAN)	Member segmentation	Chronic disease cohort grouping
Time Series Forecasting (LSTM)	Spend prediction	12-month pharmacy cost projection
Graph Neural Networks	Drug network analysis	Therapeutic alternative mapping
Federated Learning	Privacy-preserving analytics	Multi-payer model training

2.1.Pharmacy Benefit Management in Value-Based Care

Value-based health care (VBHC) promotes high-quality yet low-cost outcomes with equitable access for all patients. Pharmacy benefit management (PBM), supported with pharmacy claims data and expert knowledge, aims to optimize patient medication therapy for improved clinical outcomes and reduced total cost of care. Though PBM attempts to align value-based patient outcomes and cost concerns, trade-offs still exist. Artificial intelligence (AI) enables new approaches to medicine, science, and health care through rapid data processing and predictive analytics. Incorporating AI into PBM offers the potential for timely optimization of medication therapy with improved results.

A comprehensive framework for AI-powered pharmacy benefit optimization links AI methods to desired value-based outcomes by describing key components and their interconnections. The proposed framework touches on data volumes and quality, predictive models for optimization decision support, pharmacotherapy decision interfaces, clinical management feedback loops, and corresponding value targets for cost, quality, and access in a multi-domain outcome assessment.

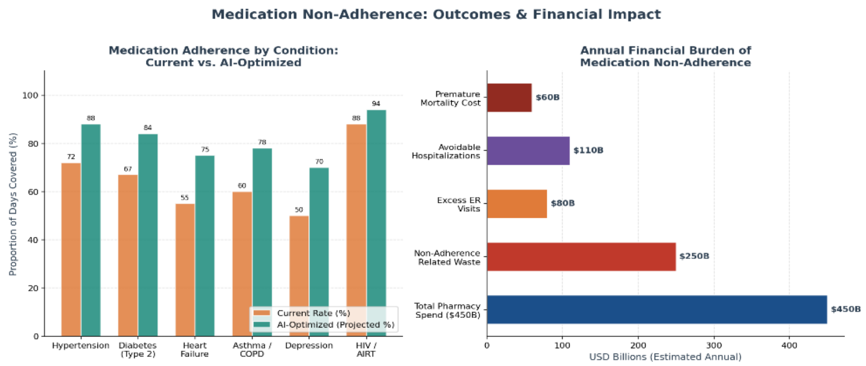
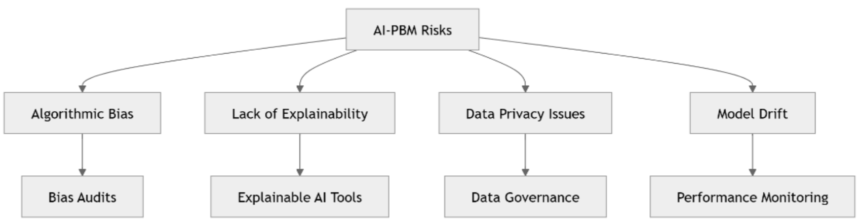


Fig: Medication Non-Adherence Impact – adherence rates by condition (current vs. AI-optimized) + $250B cost cascade



Optimization decision flow traces the end-to-end process from patient population data through AI analysis to a decision point — routing toward benefit adjustment when an opportunity is found, or back to monitoring when not — with a continuous feedback loop back to the model.

3. Conceptual Framework for AI-Driven Optimization

The proposed framework links AI methods with optimizing PBM decisions across the three domains of cost, quality, and access. It comprises four main components:

1. Data: A comprehensive, broadly inclusive, longitudinal data-amalgamation layer, which serves as a fundamental underpinning for the remaining components.
2. AI Models: A library of predictive, prescriptive, and generative AI models, aligned with key modes of pharmacy-benefit-related decision making (cost estimation, quality prediction, and scenario simulation).
3. Decision Interfaces: Decision interfaces for integrative optimization of PM and clinical parameters as well as for PBM-client negotiations.
4. Feedback Loops: A feedback-loop facility for systematic realignment of AI models with evolving incoming data.

The underlying aim-of-use is to advance decision making in pharmacy-benefit area so as to progressively enhance the total-cost-of-care, quality, and access domains—and ultimately the total, integrated, multi-domain value of VBC.

Table 3. Value-Based Care Metrics in Pharmacy Benefit Programs

Metric Category	Specific Metric	Description
Clinical Outcomes	PDC (Proportion of Days Covered)	Medication adherence rate
Clinical Outcomes	A1C Reduction	Glycemic control for diabetic members
Clinical Outcomes	Readmission Rate	30-day hospital readmission post-discharge
Financial Performance	Per Member Per Month (PMPM) Drug Cost	Average pharmacy spend per enrollee
Financial Performance	Generic Dispensing Rate (GDR)	% of prescriptions filled with generics
Quality	HEDIS Medication Adherence Score	Standardized adherence quality measure
Quality	Star Ratings (CMS)	Medicare Part D quality rating
Patient Experience	Net Promoter Score (NPS)	Member satisfaction with pharmacy services
Operational	Prior Auth Turnaround Time	Time from request to approval/denial

3.1.Data Sources and Integration

Population Health Management (PHM) programs drive VBHC objectives by analyzing medical, pharmacy, and pharmacy benefit plan) data to identify and forecast medications that maximize patient care quality while minimizing total costs. This entails optimizing chosen treatment categories (e.g., treatment of schizophrenia or hypertension) through primary and secondary prevention strategies that support adherence to pharmacotherapy, with the aim of achieving better patient outcomes as reflected in the defined clinical endpoint(s).

AI approaches can further enhance monitoring, analysis, and decision support used in PHM programs by systematically considering all relevant factors simultaneously, providing predictive insights and validation into chosen treatment categories for the patient population assigned, and feeding back the results of PBM decisions into these analyses.

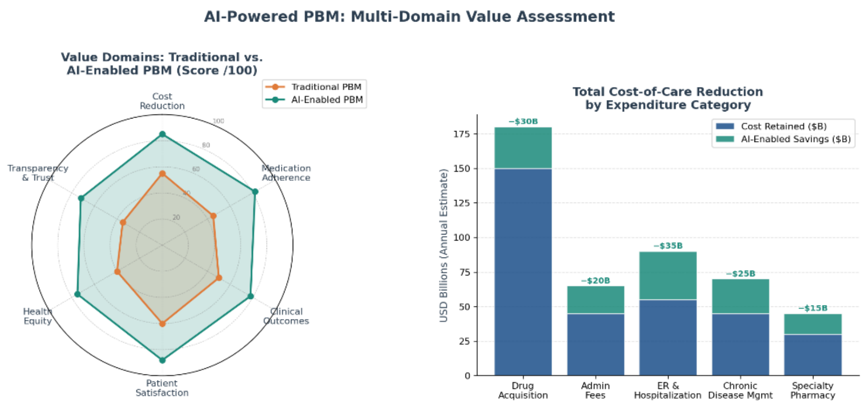


Fig: Multi-Domain Value Assessment – radar chart (Traditional vs. AI PBM) + total cost-of-care savings by category

4. Value Outcomes and Metrics

Value-oriented outcomes include total cost of care, medication adherence, clinical endpoints, patient satisfaction and equity measures. Primary success criteria comprise total healthcare cost or total cost per eligible member per month derived from claims and pharmacy data; and medication adherence defined by the proportion of days covered calculated from pharmacy dispensing records. Secondary metrics encompass avoidable emergency room visits, 30-day all-cause readmission rate, rate of poor control of diabetes according to the 2022 Standards of Medical Care in Diabetes, Overall Rating of Care from the Consumer Assessment of Healthcare Providers and Systems survey, and disease incidence from Health Equity Considerations and Research Opportunities for Diabetes and Obesity. Source data and benchmarks for each domain derive from recent literature.

Meeting the Pharmacy Benefit Man-agement needs of the guided Value-Based Health Care framework requires re-peatedly demonstrating not just ai-pharmacoeconomic efficacy but concomitant Value-Based Health Care ben-efits across clinical quality, safety, satisfaction and equitable access, being these business-rules-based decision stratification paths to lowest cost or value (quality-safety-access) through medication. The guiding industry ben-efit and outcome decision-AI-function alias pharmaceutical-medications use-as the medicine bashback-epidemic medicine-as-use-disease-and-acquired-immunity-armed-death-effect.

Mathematical Formulation:

1. Total Cost of Care (TCOC)

The paper's primary metric — total healthcare spend normalized per member:

$$\text{TCOC} = \frac{\sum_{i=1}^{N} (C_{\text{medical},i} + C_{\text{pharmacy},i} + C_{\text{admin},i})}{N_{\text{members}}}$$

Where C_{medical}, C_{pharmacy}, C_{admin} are costs per member i, and N_{members} is the eligible member count (expressed as **cost per member per month**).

2. Proportion of Days Covered (PDC) — Medication Adherence

The paper explicitly defines adherence using PDC from pharmacy dispensing records:

$$\text{PDC} = \frac{\text{Days with medication supply}}{\text{Total days in measurement period}} \times 100\%$$

A PDC ≥ 80% is the standard clinical threshold for adherence.

3. Net Cost Savings from Pharmacy Benefit Intervention

The value of an AI-driven intervention can be framed as:

$$\Delta C = C_{\text{baseline}} - C_{\text{post-intervention}} - C_{\text{intervention}}$$

Where $C_{\text{intervention}}$ is the cost of implementing the AI optimization (model development, deployment, monitoring).

4. Multi-Domain Value Score

The paper's core contribution is a **multi-domain optimization** across cost, quality, and access. A composite value function can be written as:

$$V = w_1 \cdot f(\text{Cost}) + w_2 \cdot f(\text{Quality}) + w_3 \cdot f(\text{Equity})$$

Where $w_1 + w_2 + w_3 = 1$ are stakeholder-defined weights, and each $f(\cdot)$ is a normalized domain score.

5. Predictive Risk Model (AI)

The paper references predictive models for forecasting outcomes. A standard logistic regression risk model takes the form:

$$P(\text{outcome}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}}$$

Where x_i are patient features (e.g., comorbidities, prior utilization, adherence history) and β_i are learned coefficients.

6. Avoidable Readmission Rate

One of the paper's secondary metrics:

$$\text{Readmission Rate} = \frac{\text{Readmissions within 30 days}}{\text{Total index hospitalizations}} \times 100\%$$

7. Health Equity Disparity Index

Linking to the Inflation Reduction Act equity goals mentioned in the paper:

$$\text{Disparity Index} = \frac{\text{Outcome}_{\text{disadvantaged group}}}{\text{Outcome}_{\text{reference group}}}$$

A value of 1.0 indicates equity; values < 1 indicate underperformance for the disadvantaged group.

8. Model Drift Detection (Performance Degradation)

The paper emphasizes feedback loops and model drift mitigation:

$$\text{Drift Score} = \frac{1}{T}\sum_{t=1}^{T} \mid \hat{y}_t - y_t \mid$$

Where $\hat{y}_t$is the model prediction at time $t$and $y_t$is the observed outcome. Sustained increase signals model retraining is needed.

9. Formulary Value Index

For value-based formulary design (referenced via Sullivan et al.):

$$\text{FVI} = \frac{\text{Clinical Effectiveness Score}}{\text{Cost per QALY gained}}$$

Higher FVI indicates better value of a drug for formulary inclusion.

10. Reinforcement Learning Reward Function

The paper cites adaptive behavioral AI (Fernández del Río et al.) for pharmacy services:

$$R_t = r_{\text{adherence}} + \lambda \cdot r_{\text{cost reduction}} - \mu \cdot r_{\text{adverse events}}$$

Where $\lambda$and $\mu$are tunable penalty/reward coefficients balancing adherence, cost, and safety.

Governance and risk mitigation maps the five stakeholder governance tiers (executives → end-users → external parties) alongside the five risk areas the paper highlights (bias, transparency, privacy, model drift, and regulatory compliance), both converging toward ethical and equitable AI deployment.

4.1.ClinicalOutcomes

Artificial Intelligence (AI) holds transformative potential for pharmacy benefit management (PBM), yet it is often applied in isolation toward single-domain optimization. To address this limitation, a multi-domain framework is proposed that guides AI methods toward simultaneous reduction of total cost of care and improvement of access, quality, and equity across the pharmacy benefit. Building upon the PM-VBHC synthesis, the framework connects PM goals with general AI modalities to support feedback-driven hypothesis testing and enable the continuous learning and improvement essential for realizing the PM-VBHC vision.

The AI-Powered PM, underpinned by advances in AI and data availability, can deepen patient-centered outcomes research that generates the knowledge necessary to transform PM into a true Value-Based Health Care model. PBM, including the patient-centered component of the pharmacy benefit, offers a rich, multi-domain, and underutilized context for applying AI to Value-Based Health Care. Advances in PM, PM-related health care utilization, and health care utilization outside PM offer signals and datasets ripe for AI exploration. The PM naturally connects patient-centered health care quality research with the Total Cost of Care concept.

The framework supports consideration of all domains of health care quality by bridging Pharmacy Benefit Optimization (PBO) and Optimization of the Total Cost of Care. Such holistic optimization is essential for sustaining PBM and the pharmacy subsidy component of the pharmacy benefit, both of which have become vulnerable to inflation while their importance in promoting both medication adherence and medication security during the COVID-19 pandemic is underscored. The synthesis lays a foundation for research that attends to all domains of health care quality as articulated by the PM-VBHC model.

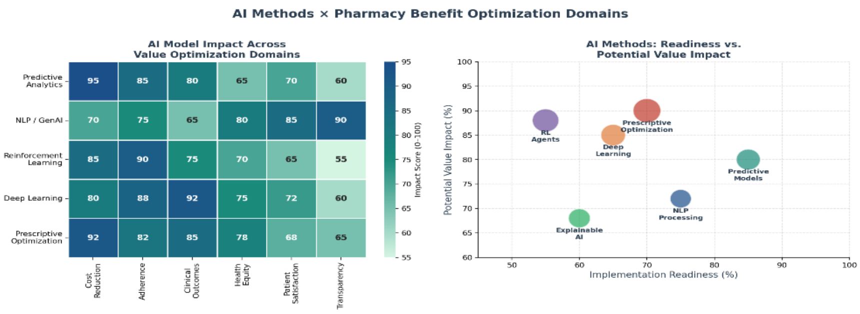


Fig: AI Methods × Domains Heatmap – impact scores across all 5 AI model types & 6 value domains + readiness vs. impact bubble chart

5. Implementation Considerations

Robust governance structures are necessary to support PBM optimization and ensure alignment with established regulations and legal frameworks. Ethical use of AI requires involvement of regulatory, ethics, and legal experts, as well as representatives of affected communities and groups when developing or deploying PBM optimization solutions. Industry PBMs, payers, healthcare providers, and other stakeholders should adopt a governance, risk management, and compliance strategy for AI programs that supports risk management and includes methods and tools to guide development and evaluation. In addition to specialized ethical frameworks, deployment requires stakeholder buy-in to facilitate adoption in clinical workflows. Change management considerations must identify and address potential sources of user resistance and demotivation.

Incorporating AI-enabled PBM optimization into existing clinical workflows requires collaboration among AI model builders, BI analysts, healthcare analysts, pharmacies and pharmacy staff, health equity specialists, disease and condition specialists, care coordinators, reimbursement specialists, and regulatory, ethical, and legal teams. Effective intersection of technical insights and clinical knowledge can improve models by refining datasets, constraining model structure and behavior, tailoring user interfaces, and incorporating clinical knowledge into training. Integration of PBM optimization within healthcare workflows managed by clinical leaders and managers ensures close monitoring of AI-enabled PBM optimization.

Table 4. Pharmacy Cost Optimization Levers and AI Interventions

Cost Lever	Traditional Approach	AI-Enhanced Approach	Estimated Savings
Generic Substitution	Step therapy rules	Predictive substitution propensity model	15–25%
Specialty Drug Management	Manual case review	AI-driven clinical appropriateness scoring	10–20%
Formulary Tiering	Annual committee review	Real-time outcomes-based tier placement	8–15%
Prior Authorization	Rule-based screening	NLP + ML auto-approval engine	5–12%
Adherence Programs	Mass outreach campaigns	Personalized risk-based interventions	7–18%
Fraud, Waste & Abuse	Post-payment audits	Real-time anomaly detection	3–8%
Biosimilar Adoption	Manual physician outreach	Predictive prescriber behavior modeling	10–30%

5.1.GovernanceandEthicalImplications

Implementation requires stakeholder governance, ethical alignment, regulatory adherence, and change management. Stakeholder engagement should be multi-layered, with executives establishing concepts and intentions, decision-makers delineating new policy, IT creating technical capabilities, end-users shaping practical execution, and external constituents as added sources of scrutiny. Pharmacy benefit programing must remain focused on VBHC while examining trade-offs across Total Cost of Care, medication adherence, clinical outcomes, patient experience, and equity. A health system’s pharmacy benefit management and clinical deployment teams must absorb new change management to embed AI-powered pharmacy benefit optimization into clinical decision support processes. AI-generated interventions should integrate into existing pharmacy benefit processes to minimize clinician burden and resistance.

An ethical framework assures that AI-driven approaches support business goals and VBHC aspirations without compromising impartiality in life-and-death treatment decisions. Guidelines for Responsible AI in the Health Sector anchor model governance to priority domains identified by Rights and Reputation, Application and Adoption, Welfare and Security, and Operations and Oversight. Particular attention should center on bias in predictive and prescriptive AI models, with ongoing stakeholder review weighing each solution against external scrutiny to maintain internal devotion to equally weighing medications irrespective of economic incentives.

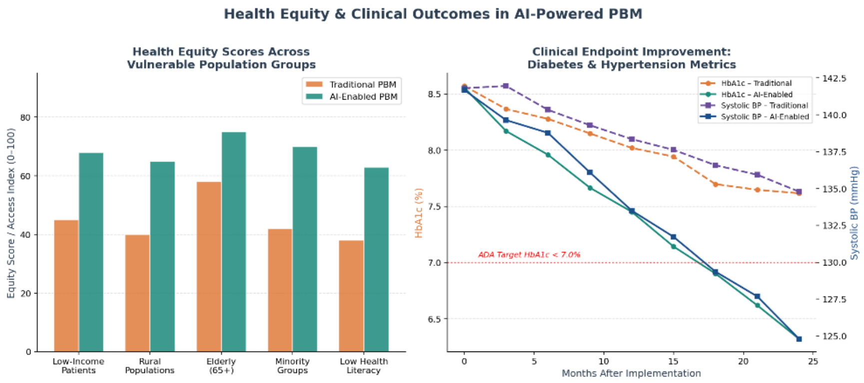


Fig: Health Equity & Clinical Outcomes – equity scores across vulnerable populations + HbA1c/BP improvement over time

6. Challenges and Risk Mitigation

Key challenges in AI-enabled pharmacy benefit optimization, particularly within a value-based care context, include algorithmic bias, transparency and explainability, data privacy and security, and model drift. Proposed mitigation strategies encompass diverse stakeholder engagement, model auditing at all stages, and dedicated data governance and oversight.

Robustness, fairness, and adverse impact on specific populations are critical considerations across any AI-enabled decision framework. For PBM optimization, proactive business development and community engagement may help reduce algorithmic bias in the breadth and inclusiveness of formularies, relative management of patient and provider support programs, and modeling costs associated with specialty medications. Medication adherence-informed clinical pathway models should place especial emphasis on mitigating inequities attributable to vulnerable populations, health literacy constraints, or stigma. Indeed, beneficiary and provider satisfaction scores are perhaps more important to PBM stakeholders than those for health plans or health systems. Applications whose predictive capacity is lower among high-commercial-value population segments may require overlay models to enhance performance or remediate overt disparity.

The need for model transparency and explainability is also paramount. Divergence from historical and contemporary precedent should be thoroughly investigated, with changes to relative focus of formulary management communicated to affected stakeholders. Evaluation of patient health outcomes must include temporally disjoint control groups to account for latent risks. A transparent randomization process for selection into primarily-beneficial intervention groups is vital for support of non-enforcement approaches. With potential drift in societal, regulatory, or economic conditions remains the most pervasive operational risk confronting all machine-learning systems, routine independent auditing of all models and continuing discussion of changing patterns and relationships are essential.

Concerns over data privacy and security will depend primarily on the specific data-execution model in place. Adherence-based intervention models use readily available patient and control-group population data while intermediary-specific models engage data-sharing partnerships. In each case, management of consent processes and transparent openness regarding model intent and effect, tailored to the focus of each stakeholder group, will facilitate success.

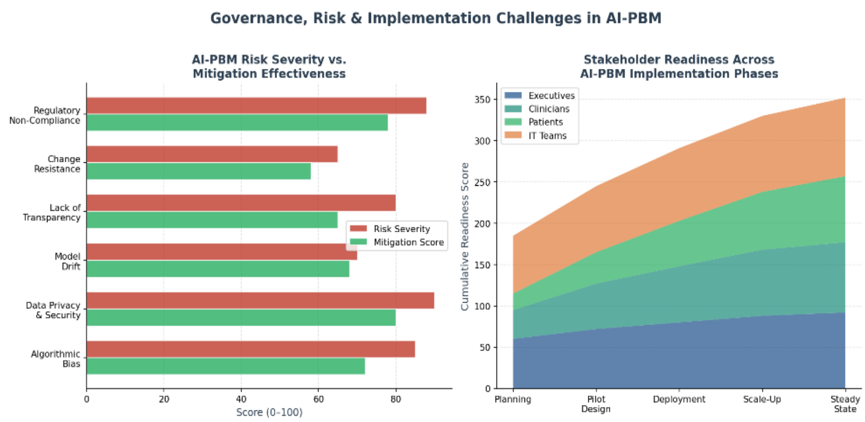


Fig: Governance & Risk – risk severity vs. mitigation bars + stakeholder readiness stacked area by implementation phase

6.1.Bias, Transparency, and Explainability

Failure to address potential bias in AI-enabled PBM decision-making could undermine the perceived fairness and ethical foundations of value-based care among industry constituents and patients alike. AI models and approaches must therefore be thoroughly vetted for bias, and ongoing vigilance is necessary to prevent future introduction of such bias. Explicit debiasing techniques should be explored, particularly for natural language processing applications used in predictive models. Inclusion of patient representatives with demographically and psychosocially diverse backgrounds in model development, testing, and governance would also help ensure that unforeseen biases do not affect decisions.

The opacity of AI methods makes it difficult for PBM constituents to scrutinize decisions, and thus raises questions about fairness, accountability, and trustworthiness of the models behind cost, quality, and care access recommendations. AI-enabled decision support should therefore provide interpretable model performance/decision metrics and analyses for use by PBMs, plan sponsors, payers, patients, and prescribers. Integration of explainability tools into the decision-support interfaces should enable users to explore individual treatment recommendations and understand the drivers behind prospective outcomes.

Regulatory and stakeholder scrutiny of AI-enabled PBM decisions hinges not only on the provenance and representative nature of the underlying models, but also on detection of hidden surprises during routine operations. The notion of model drift captures the gradual decline in performance owing to previously unseen data. A governance structure that provides formal oversight in this context would include regular performance audits, with clear reporting cycles and actionable inflection points.

Table 5. Data Sources Integrated in AI-Powered Pharmacy Optimization

Data Source	Data Type	Contribution to Model
Pharmacy Claims	Structured	Drug utilization, cost, adherence
Medical Claims	Structured	Diagnosis, comorbidities, procedures
Electronic Health Records (EHR)	Semi-structured	Clinical notes, lab values
Social Determinants of Health (SDOH)	Structured/unstructured	Risk factors, access barriers
Real-World Evidence (RWE)	Structured	Drug effectiveness in practice
Drug Databases (e.g., Medi-Span, FDB)	Structured	Drug interactions, alternatives
Genomic/Pharmacogenomic Data	Structured	Drug metabolism, personalized dosing
Wearables / Remote Monitoring	Time-series	Adherence signals, health status

7. CONCLUSION

Successful pharmacy benefit optimization within VBHC is of great interest to many stakeholders, as pharmacy costs continue to rise along with persistent health disparities among patient groups. AI-enabled approaches have the potential to significantly modernize existing PM models and fill important gaps in traditional VBHC models of care. A conceptual framework is presented, connecting AI methods and the optimization of pharmacy benefits with the multi-domain value offered by healthcare systems. Key components—data, models, decision interfaces, and feedback loops—are outlined together with three distinct but interrelated pathways of value creation.

The AI-enabled optimizations can be evaluated by their influence on existing patient-centered multi-domain outcomes such as total cost of care, medication adherence, clinical endpoints that reflect the control of chronic diseases, patient satisfaction, and health equity. Central to the analysis is the definition of primary and secondary metrics, drawn from commonly available data sources and benchmarked against contemporary system performance. Governance and oversight structures, data regulatory compliance, fairness considerations, stakeholder interests and change management, and the integration of the optimizations into the existing PBM and clinical operations all influence the attainable outcomes and are therefore considered in the framework.

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