Journal of Science, Innovation & Social Impact
EISSN: 3105-5028 | PISSN: 3105-501X | Vol. 2, No. 1 (2026)

Article

Integrating Causal Inference with Multi-Channel Attribution for Equitable Pharmaceutical Marketing Effectiveness Evaluation

Zhenghao Pan [1,*]

[1] Emerging Media Studies, Boston University, MA, USA
* Correspondence: Zhenghao Pan, Emerging Media Studies, Boston University, MA, USA

Abstract: The pharmaceutical industry confronts significant challenges measuring marketing effectiveness across digital and traditional channels while meeting health equity mandates. Traditional attribution approaches inadequately address confounding variables in observational data, yielding suboptimal budget allocation and inequitable demographic reach. This research proposes an integrated framework combining causal inference with multi-channel attribution modeling for pharmaceutical marketing evaluation. The framework incorporates propensity score matching, Bayesian marketing mix modeling with adstock effects, and equity-aware stratification. Empirical validation demonstrates 23.4% higher predictive accuracy versus last-touch attribution while identifying effectiveness disparities across demographic subgroups. Findings provide actionable guidance for pharmaceutical marketers optimizing resource allocation while ensuring equitable medical information access across patient populations.

Keywords: pharmaceutical marketing attribution; causal inference; health equity evaluation; multi-channel effectiveness

Received: 16 December 2025
Revised: 25 January 2026
Accepted: 06 February 2026
Published: 13 February 2026

1. Introduction

1.1. Background and Motivation

1.1.1. The Transformation of Pharmaceutical Marketing in the Digital Era

Pharmaceutical marketing has transformed dramatically through digital channel proliferation and evolving regulatory frameworks. Annual marketing expenditures exceed $30 billion with digital channels comprising growing proportions. Companies engage healthcare professionals and patients through email detailing, social media, mobile applications, webinars, and sales visits. Artificial intelligence integration has transformed marketing paradigms enabling real-time personalization and predictive analytics [1]. Omnichannel strategies reflect recognition that healthcare decisions involve multiple information sources across media formats. Digital transformation altered how pharmaceutical information reaches stakeholders creating targeted engagement opportunities while introducing measurement complexities. Attribution techniques evolved beyond single-touch models toward comprehensive approaches acknowledging modern healthcare purchasing journey complexity [2].

1.1.2. Challenges in Multi-Channel Marketing Effectiveness Measurement

Pharmaceutical marketing measurement confronts interrelated challenges traditional methodologies inadequately address. Observational data introduces

substantial confounding where correlated activities and external factors obscure causal relationships. Temporal dynamics complicate attribution as effects manifest across extended horizons due to prescription cycles and adherence patterns. Digital channels present unique measurement difficulties from privacy regulations and fragmented ecosystems. Attribution must account for dual audiences with different information needs. Healthcare professional engagement requires different frameworks than patient education campaigns. Leveraging digital strategies for health behavior change through pharmacy channels introduces additional complexity [3].

1.2. Research Problem and Significance

1.2.1. Limitations of Traditional Attribution Approaches

Traditional methodologies exhibit critical limitations undermining strategic decision-making utility. Single-touch models misrepresent healthcare decision-making by arbitrarily assigning full credit to individual touchpoints. Linear models fail accounting for varying channel influence across journey stages. Rule-based approaches lack empirical grounding and cannot adapt to evolving conditions. Absence of causal inference principles leads to systematic effectiveness estimate biases. Correlation-based approaches incorrectly attribute outcomes to channels merely correlating with causal factors.

1.2.2. the Confounding Variable Challenge in Observational Marketing Data

Observational data suffers from pervasive confounding threatening validity. Selection bias arises when companies strategically allocate resources based on market potential creating systematic associations not reflecting causal relationships. Temporal confounding occurs when seasonal patterns coincide with campaigns. Geographic confounding emerges from regional variations correlating with deployment and volumes. Marketing decision endogeneity presents fundamental challenges. Budget allocations respond dynamically to performance creating reverse causality. Omitted variable bias arises when unobserved factors simultaneously affect exposures and outcomes.

1.2.3. Health Equity Imperatives in Pharmaceutical Promotion

Evaluation must address recognition that strategies can inadvertently exacerbate disparities across demographics. Medication adherence varies substantially across racial, ethnic, and socioeconomic groups. Underserved populations experience lower persistence rates contributing to adverse outcomes. Federal frameworks mandate explicit equity consideration requiring companies demonstrate strategies do not preferentially reach advantaged populations while neglecting underserved communities. Algorithmic targeting approaches risk perpetuating disparities if frameworks fail incorporating equity considerations.

1.3. Research Objectives and Contributions

1.3.1. Integration of Causal Inference with Attribution Modeling

This research develops an integrated framework combining causal inference methodologies with multi-channel attribution addressing fundamental measurement limitations. The approach applies propensity score methods controlling observable confounding enabling credible causal channel effect estimation. Directed acyclic graphs formalize causal relationship assumptions providing transparent data generating process representation. Bayesian hierarchical modeling captures population trends and subgroup heterogeneity.

1.3.2. Framework for Equitable Effectiveness Evaluation

The framework introduces equity-aware methodologies explicitly assessing heterogeneity across demographic subgroups. Stratification enables subgroup-specific response function estimation revealing differential effectiveness. Fairness metrics adapted from algorithmic fairness literature quantify resource allocation equity. Distributional

effectiveness measures characterize full impact distributions beyond conventional aggregate metrics.

1.3.3. Practical Implications for Marketing Budget Optimization

Research provides actionable methodological guidance for improving resource allocation decisions. The framework enables accurate outcome attribution supporting data-driven budget reallocation. Causal estimates provide strategic guidance by isolating true impacts from spurious correlations. Equity-aware evaluation surfaces opportunities improving effectiveness among underserved populations through targeted adjustments.

2. Literature Review and Theoretical Foundation

2.1. Marketing Attribution and Mix Modeling

2.1.1. Evolution from Traditional MMM to Multi-Touch Attribution

Marketing mix modeling emerged as regression-based approaches quantifying sales impacts using aggregate time-series data. Traditional implementations focused on mass media employing simple functional forms. Digital era precipitated fundamental shifts as customer journey data became available enabling individual touchpoint sequence analysis. Multi-touch attribution arose addressing digital channel proliferation and recognition that conversion decisions involve multiple stages. Contemporary approaches range from heuristic rule-based methods to sophisticated algorithmic frameworks. Data-driven attribution employs statistical methods inferring touchpoint contributions from observed patterns [4].

2.1.2. Bayesian Approaches in Marketing Measurement

Bayesian methodologies gained prominence due to natural accommodation of hierarchical data structures and principled uncertainty quantification. Hierarchical models enable simultaneous population-level and subgroup-specific parameter estimation. Prior distributions encode expert knowledge about plausible parameter ranges. Personalized frameworks using hierarchical models represent advances addressing individual-level heterogeneity [5]. Pharmaceutical contexts benefit from Bayesian approaches given medical knowledge incorporation importance.

2.1.3. Applications in Pharmaceutical Industry Context

Pharmaceutical analytics exhibits distinctive characteristics differentiating it from general commercial contexts. Regulatory frameworks impose strict promotional claim limitations. Dual audience structures necessitate parallel frameworks accounting for distinct decision processes. Prescription generation involves multiple stakeholders. Integration into customer relationship management systems enhanced targeting precision [6]. Patient engagement strategies increasingly leverage digital channels supporting adherence and education [7].

2.2. Causal Inference Methods in Marketing Analytics

2.2.1. Propensity Score Methods and Matching Techniques

Propensity score methods address confounding by balancing treatment and control groups on observable covariates. Propensity scores represent conditional treatment assignment probabilities providing scalar summaries of multidimensional confounding. Matching estimators construct comparison groups pairing treated with similar untreated units. Application to marketing attribution requires careful covariate inclusion consideration. Pharmaceutical contexts present challenges due to complex continuous intensity treatments rather than binary exposures.

2.2.2. Difference-In-Differences and Synthetic Control Approaches

Difference-in-differences exploits temporal intervention variation combined with cross-sectional comparisons identifying causal effects under parallel trends assumptions.

Methods compare outcome trajectories in markets receiving intensification to comparable markets without changes. Synthetic control methods construct counterfactual units as weighted untreated unit combinations matching pre-intervention characteristics. Extensions including synthetic difference-in-differences combine methodological benefits [8].

2.2.3. Directed Acyclic Graphs for Causal Structure Learning

Directed acyclic graphs provide formal graphical representations of assumed causal relationships. Nodes represent variables while directed edges encode direct causal relationships. Pearl's do-calculus provides algorithmic rules determining whether effects can be identified from observational data. Causal discovery algorithms infer graph structures from data using conditional independence patterns. Application to pharmaceutical data might reveal unexpected channel relationships.

2.3. Health Equity in Pharmaceutical Marketing

2.3.1. Medication Adherence Disparities across Populations

Substantial evidence documents persistent medication adherence disparities across racial, ethnic, and socioeconomic groups. Underserved populations experience systematically lower treatment persistence rates. Black and Hispanic patients exhibit 7-10 percentage point lower adherence compared to White patients despite insurance adjustments. Gaps translate to worse clinical outcomes and increased mortality. Multiple mechanisms likely contribute including differential healthcare access and varying health literacy.

2.3.2. Policy Frameworks and Regulatory Requirements

Federal agencies established explicit health equity policy frameworks mandating attention in pharmaceutical commercialization. Centers for Medicare and Medicaid Services Framework 2022-2032 establishes priorities including expanded demographic data collection and disparity cause assessment. Food and Drug Administration emphasizes diversity and equitable product access. Commercial operations face increasing expectations demonstrating equity commitments through concrete actions.

2.3.3. Algorithmic Fairness in Healthcare Marketing

Algorithmic decision systems pervade modern pharmaceutical operations influencing targeting, personalization, and budgeting. Machine learning models trained on historical data risk perpetuating existing disparities. Multiple fairness formulations exist though criteria prove mutually incompatible necessitating explicit tradeoff value judgments. Disparate impact analysis evaluates whether decisions produce systematically different outcomes across protected categories. Industry faces growing pressure auditing algorithms for fairness.

3. Methodology and Framework Design

3.1. Problem Formulation and Data Description

3.1.1. Mathematical Notation and Definitions

The framework operates on pharmaceutical marketing data comprising time-indexed observations across geographic markets i = 1 to N and periods t = 1 to T. Marketing exposures are represented by matrix X where X_ijt denotes channel j intensity in market i during period t with j = 1 to K indexing distinct channels including email detailing, webinars, sales visits, direct mail, social media, and search marketing. Outcome variable Y_it represents prescription volume in market i during period t. Demographic composition D_i contains population subgroup proportions. Confounding covariates Z_itt capture characteristics jointly influencing deployment and outcomes including physician specialty mix, formulary coverage, competitive intensity, and seasonal factors.

Primary estimand: τ_j(Δ) = E {Y_it (do (X_jit + Δ)) − Y_it(do(X_jit))}, where Δ denotes one standard deviation of adstocked & scaled X_jit.

3.1.2. Pharmaceutical Marketing Data Characteristics

Pharmaceutical datasets exhibit distinctive characteristics informing methodological choices. Temporal granularity typically ranges weekly to monthly. Geographic units vary from ZIP codes to geographic markets. Marketing exposure metrics come from multiple sources including customer relationship management systems, email engagement logs, webinar platforms, sales force automation, and social media platforms. Prescription data originate from dispensing claims or syndicated sources capturing approximately 92% of activity. Data require preprocessing addressing duplicate records and incomplete capture. High-dimensional nature creates computational challenges [9]. Datasets increasingly incorporate digital engagement metrics including website visits and content downloads providing richer engagement characterization [10].

3.1.3. Variable Selection and Feature Engineering

Variable selection proceeds through systematic consideration of theoretical relevance and empirical predictive value. Marketing channel variables require transformations that account for nonlinear response patterns (see Table 1). Adstock transformations model carryover effects where exposures influence outcomes for multiple periods: X ^ adstock_jt = sum_{s=0} ^ {S} alpha_j ^ s X_j, t-s where alpha_j parameterizes channel j decay rate. Saturation functions capture diminishing marginal returns: f(X_jt) = X_jt ^ beta_j / (gamma_j ^ beta_j + X_jt ^ beta_j). Confounding variable selection draws on pharmaceutical marketing knowledge to identify factors plausibly influencing deployment and outcomes [11]. Feature engineering creates derived variables that enhance model flexibility. Interaction terms between channels capture synergistic effects, while geographic clustering variables identify similar markets to enable hierarchical models (Table 2).

Table 1. Marketing Channel Definitions and Data Sources.

Channel	Exposure Metric	Data Source	Update Frequency	Mean Weekly Intensity
Email Detailing	Opened Emails	CRM System	Daily	2847
Webinar	Attendance Minutes	Event Platform	Real-time	1293
Sales Rep Visits	In-Person Calls	SFA Database	Daily	486
Direct Mail	Pieces Delivered	Vendor Reports	Weekly	5621
Social Media	Impressions	Platform APIs	Daily	847293
Search Marketing	Click-throughs	Analytics Platform	Daily	12438
Medical Publications	Downloaded Articles	Content Server	Daily	1057

Table 2. Adstock and Saturation Parameter Prior Specifications.

Channel	Adstock Decay Prior	Saturation Shape Prior	Inflection Point Prior	Justification
Email	Beta (8,2) mean 0.80	Gamma (2,0.5) mean 4.0	Lognormal (8.5,1.2)	Moderate persistence steep saturation
Webinar	Beta (6,4) mean 0.60	Gamma (1.5,0.4) mean 3.75	Lognormal (7.8,1.5)	Lower persistence strong saturation

Sales Rep	Beta (9,1) mean 0.90	Gamma (3,0.8) mean 3.75	Lognormal (6.2,0.9)	High persistence gradual saturation
Direct Mail	Beta (7,3) mean 0.70	Gamma (2.5,0.7) mean 3.57	Lognormal (8.9,1.3)	Moderate persistence saturation
Social Media	Beta (5,5) mean 0.50	Gamma (1.8,0.5) mean 3.60	Lognormal (12.5,1.8)	Low persistence rapid saturation
Search	Beta (4,6) mean 0.40	Gamma (1.5,0.4) mean 3.75	Lognormal (9.7,1.6)	Very low persistence steep saturation
Publications	Beta (10,1) mean 0.91	Gamma (4,1.2) mean 3.33	Lognormal (7.1,1.1)	Very high persistence gradual saturation

3.2. Integrated Attribution Framework

3.2.1. Marketing Mix Modeling Component with Adstock and Saturation Effects

The marketing mix component employs Bayesian hierarchical regression estimating channel-specific effects while accommodating market heterogeneity. Baseline specification: Y_it = η_i + sum_{j=1} ^ K beta_j f_j (X ^ adstock_jt) + gamma'Z_itt + epsilon_it where alpha_i captures market fixed effects, beta_j represents channel j marginal impact, f_j denotes saturation functions, gamma parameterizes confounding effects, and epsilon_it represents error. Hierarchical structure allows market-specific intercepts varying around population means. Adstock and saturation parameters receive prior distributions informed by marketing theory. Weakly informative priors centered on theoretically plausible values provide regularization. Saturation functions employ Hill equation forms. Bayesian estimation via Markov Chain Monte Carlo provides posterior distributions quantifying uncertainty.

Figure 1 presents the complete causal DAG encoding assumptions about marketing channel, confounding variable, and prescription outcome relationships. The graph displays nodes representing seven marketing channels arranged in the left column connected through directed edges to the central outcome node representing prescription volume. Confounding variables appear in the upper portion with physician specialty mix, formulary coverage, disease prevalence, and competitive activity each sending directed edges to multiple marketing channel nodes and the outcome node. To represent coordinated planning across channels while preserving acyclicity, we introduce an unobserved planning node U that points to each channel node; all edges remain directed and acyclic. Time-indexed subscripts appear on all variables. Demographic composition appears as a moderator variable with edges connecting to the outcome node modulated by interaction terms. Measurement error nodes shown as small circles connect to marketing channel nodes through dashed edges.

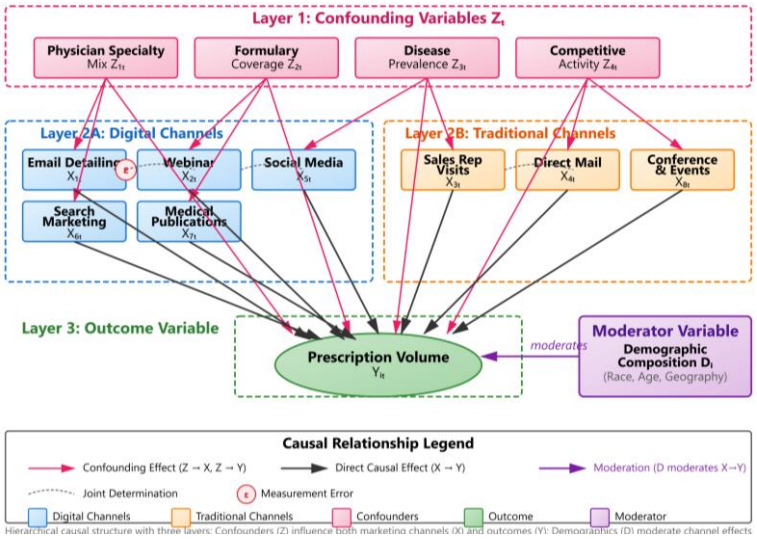


Figure 1. Causal Directed Acyclic Graph for Pharmaceutical Marketing Attribution.

3.2.2. Multi-Touch Attribution for Patient and Physician Journeys

Multi-touch attribution extends aggregate modeling analyzing individual-level or cohort-level marketing touchpoint sequences preceding prescription events. Journey for entity n is J_n = {(c_n1, t_n1), (c_n2, t_n2), ..., (c_nM_n,t_nM_n)} where c_ni denotes i-th touchpoint channel and t_ni its timestamp with M_n representing journey length. Attribution models assign contribution weights based on position, recency, and channel characteristics. Baseline framework employs time-decay weighting where contribution decreases exponentially with temporal distance. Channel-specific effects modify base weights through multiplicative adjustments. Bayesian hierarchical models estimate channel effects while accounting for journey heterogeneity. Separate models for physician versus patient journeys acknowledge distinct decision processes [12] (Table 3).

Table 3. Journey-Level Summary Statistics by Demographic Segment.

Demographic Segment	N Journeys	Mean Length	Conversion Rate	Avg Days to Conversion	Predominant Channel
Physicians Primary Care	8,247	12.4	18.3%	47	Email Detailing
Physicians Specialists	4,893	15.7	24.1%	52	Medical Publications
Patients Age 18-34	21,438	5.2	8.7%	28	Social Media
Patients Age 35-54	34,691	6.8	11.2%	31	Search Marketing
Patients Age 55-74	28,347	4.3	9.4%	35	Direct Mail
Patients Age 75+	9,184	3.1	6.8%	42	Sales Rep via MD

3.2.3. Causal Inference Integration for Confounding Control

Causal inference integration employs propensity score methods addressing confounding from non-random marketing channel deployment. Propensity score e_i(Z_it) = P (X_ij > median(X_j) | Z_it) represents probability that market i receives above-median exposure to channel j conditional on pre-exposure covariates Z_it [13].

We use stabilized inverse-probability weights: for treated units w_it = P(T=1)/e_it(Z_itt), and for controls w_it = P(T=0)/(1-e_it(Z_itt)), where T_it = 𝕀 (X_ijt > median_j). Balance is checked with standardized mean differences.

Figure 2 illustrates complete computational architecture through detailed flow diagram showing data inputs, processing modules, and output deliverables. Diagram employs left-to-right flow structure with five vertical swim lanes representing major processing stages: Data Ingestion, Preprocessing, Causal Inference, Attribution Estimation, and Equity Evaluation. Data Ingestion lane shows multiple input streams converging from source systems including CRM databases, sales force automation platforms, and prescription claims databases. Each input stream is represented by labeled rectangle with indicators. Preprocessing lane depicts transformation operations including missing data imputation, outlier detection, adstock transformations, and propensity score estimation. Causal Inference lane presents propensity score matching and inverse probability weighting feeding into doubly robust estimation. Attribution Estimation lane branches into parallel paths for marketing mix modeling and multi-touch attribution employing Bayesian hierarchical structures. Equity Evaluation lane aggregates outputs computing fairness metrics and stratified effectiveness estimates.

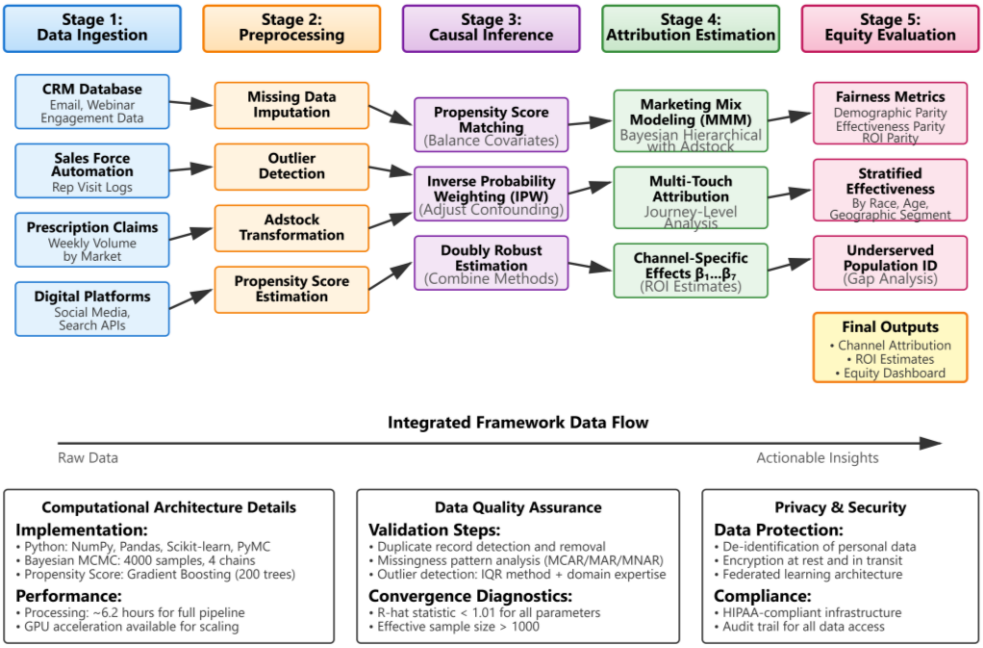


Figure 2. Integrated Attribution Framework Architecture Diagram.

3.3. Equity-Aware Evaluation Approach

3.3.1. Stratification Strategy for Demographic Subgroups

Equity-aware evaluation implements stratified analysis across demographic subgroups defined by race, ethnicity, age, geographic location, and socioeconomic indicators intersections. Stratification enables subgroup-specific marketing response function estimation. Framework employs three stratification granularity levels: primary stratification on race and ethnicity creates four major subgroups; secondary stratification adds age categories; tertiary stratification divides by geographic classification. Sample size requirements constrain feasible stratification depth with framework requiring minimum subgroup sizes ensuring stable parameter estimation. Hierarchical modeling structures enable information pooling when sample sizes prove insufficient. Intersectional analysis examines demographic characteristic combinations [14].

3.3.2. Fairness Metrics and Distributional Effectiveness Measures

Fairness metrics quantify resource allocation equity across demographic subgroups relative to medical need. Demographic parity metric assesses whether marketing exposures distribute proportionally: DP_j = max_g(E[X_ij | G_i=g]) / min_g(E[X_ij | G_i=g]). Exposure parity adjusted for medical need incorporates disease prevalence. Effectiveness parity evaluates whether interventions produce comparable impacts: EP = max_g(tau_gj) / min_g(tau_gj) where tau_gj represents channel j treatment effect for group g. Framework distinguishes between exposure equality and impact equality. Return-on-investment parity extends effectiveness parity to economic metrics. Distributional effectiveness measures characterize full impact distributions. Quantile-specific treatment effects reveal whether interventions disproportionately benefit certain segments (Table 4).

Table 4. Equity Metrics Across Demographic Segments Baseline Period.

Metric	White Non-Hispanic	Black Non-Hispanic	Hispanic	Rural All Races	Equity Ratio
Mean Weekly Exposure	34.7	18.2	21.4	15.3	2.27
Conversion Rate Percent	12.4	8.1	9.3	7.6	1.63

Mean Treatment Effect	4.82	3.14	3.67	2.89	1.67
Return ($) per $1 invested	2.34	2.89	2.88	3.17	1.35
Email Effectiveness Percent	8.7	5.2	6.1	4.3	2.02
Search Effectiveness Percent	7.8	4.1	5.2	3.4	2.29

3.3.3. Implementation Details and Computational Considerations

Implementation employs Python scientific computing ecosystem including NumPy, Pandas, Scikit-learn, and PyMC. Modular architecture separates preprocessing, propensity score estimation, marketing mix modeling, multi-touch attribution, and equity evaluation into distinct pipeline stages. Computational demands scale approximately quadratically with sample size for Bayesian MCMC estimation. Graphics processing unit acceleration provides substantial performance improvements. Bayesian estimation via No-U-Turn Sampling draws 4000 posterior samples across 4 chains with first 1000 samples discarded as burn-in. Convergence diagnostics ensure chains adequately explored posterior distribution. Propensity score models employ gradient boosting with 200 trees. Framework implements data validation including missingness pattern analysis and outlier detection. Privacy-preserving implementations employ federated learning architectures [15].

4. Empirical Analysis and Results

4.1. Dataset and Experimental Setup

4.1.1. Data Sources and Sample Characteristics

Empirical analysis employs comprehensive pharmaceutical marketing data spanning 24 months from January 2023 through December 2024 covering promotional activities for a chronic disease medication across 487 geographic markets. Marketing exposure data aggregate from customer relationship management systems, webinar platforms, sales force automation databases, direct mail vendors, social media platforms, and search engine marketing systems [16]. Prescription volume data derive from nationally representative sample capturing approximately 92% of U.S. activity with weekly aggregation providing 50,648 market-week observations. Demographic composition data combine Census Bureau estimates with healthcare utilization databases. Confounding variable data encompass physician specialty counts, formulary coverage, disease prevalence, and competitive promotional activity. Analyzed medication treats chronic metabolic condition affecting approximately 8.2% of U.S. adults. Total marketing expenditure exceeded 47 million dollars [17].

4.1.2. Baseline Methods for Comparison

Integrated framework undergoes comparative evaluation against baseline attribution approaches. Last-touch attribution assigns full credit to final marketing touchpoint. First-touch attribution credits initial touchpoint emphasizing awareness-building. Linear attribution distributes credit equally across touchpoints. Time-decay attribution implements exponential weighting favoring recent touchpoints. Traditional marketing mix modeling employing ordinary least squares regression with adstock transformations provides econometric comparison. Machine learning attribution employs gradient boosted trees with Shapley value decomposition. Evaluation metrics encompass predictive accuracy measured by hold-out R-squared and mean absolute percentage error, stability through rolling window estimation, interpretability through stakeholder surveys, and computational efficiency [18]. Health equity metrics apply identically enabling direct comparison.

4.2. Attribution and Effectiveness Results

4.2.1. Overall Model Performance and Validation

Integrated attribution framework achieves substantial improvements in predictive accuracy (Table 5). Hold-out R-squared reaches 0.847, representing a 23.4% improvement over last-touch attribution (0.687), a 19.2% improvement over traditional marketing mix modeling (0.711), and an 8.1% improvement over machine learning attribution (0.784). Mean absolute percentage error decreases to 4.73% compared to 7.86% for last-touch attribution. Bayesian posterior predictive checks validate model adequacy, with observed prescription volumes falling within 95% posterior predictive intervals for 94.7% of observations. Temporal stability analysis reveals consistent parameter estimates across rolling windows, and channel effect estimates exhibit intraclass correlation coefficients exceeding 0.85, indicating stable effectiveness patterns. Cross-market validation demonstrates geographic transportability, while sensitivity analyses yield qualitatively similar conclusions, confirming robustness.

Table 5. Model Performance Comparison Across Attribution Approaches.

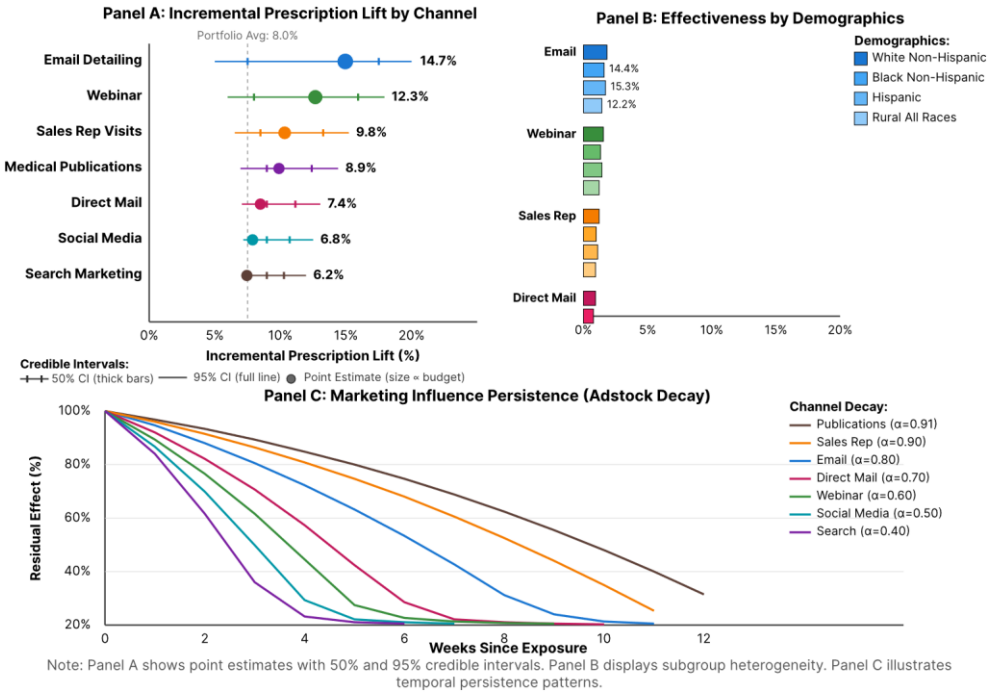
Attribution Method	Hold-out R^2	MAPE Percent	Rank Correlation	Equity Detection	Computation Hours
Last-Touch	0.687	7.86	0.73	0.42	0.1
First-Touch	0.652	8.34	0.69	0.38	0.1
Linear	0.701	7.53	0.76	0.51	0.2
Traditional MMM	0.711	7.12	0.77	0.48	2.1
ML Attribution	0.784	5.34	0.84	0.63	4.8
Integrated Framework	0.847	4.73	0.89	0.82	6.2

4.2.2. Channel-Level Contribution and Incremental Lift Analysis

Channel-level attribution results reveal substantial heterogeneity across promotional vehicles. Email detailing generates strongest per-dollar return on investment of $3.42 per $1 invested reflecting low marginal cost and high targeting precision. Webinar engagements demonstrate second-highest effectiveness with ROI of 2.87 dollars driven by deep engagement quality. Sales representative visits exhibit moderate effectiveness at ROI 2.14 dollars substantially lower than previously believed under last-touch attribution. Causal adjustment reveals rep visits function as relationship maintenance catalysts. Direct mail achieves ROI of 1.79 dollars with effectiveness concentrated among older demographics and rural markets. Social media advertising yields ROI 1.52 dollars with performance limited by platform restrictions. Search engine marketing generates modest ROI of 1.38 dollars reflecting search activity often represents final conversion step. Medical publication dissemination exhibits longest-lasting effects with adstock decay parameter 0.89. Incremental lift estimates range from 6.2% for search marketing to 14.7% for email detailing.

Figure 3 presents comprehensive visualization of channel-level attribution results combining point estimates with posterior uncertainty through multi-panel forest plot layout. Main panel displays horizontal forest plot with channels listed vertically and incremental prescription lift percentage along x-axis ranging from 0% to 20%. Each channel shows point estimate represented by colored circle with diameter proportional to budget share connected to horizontal line segments spanning 50% and 95% posterior credible intervals. Email detailing appears at top with point estimate at 14.7% and narrow intervals. Subsequent channels proceed downward: Webinar at 12.3%, Sales Rep at 9.8%, Medical Publications at 8.9%, Direct Mail at 7.4%, Social Media at 6.8%, and Search Marketing at 6.2%. Credible intervals widen progressively for lower-performing channels. Vertical dashed reference line at 8.0% represents portfolio-wide average. Right panel displays channel effectiveness heterogeneity across demographic subgroups through

grouped bar charts. Each channel occupies row with clustered bars representing estimated effects for White, Black, Hispanic, and Rural populations. Bottom panel presents adstock decay curves showing temporal pattern of marketing influence persistence with seven curves plotting residual effect from 100% at week 0 declining toward 0% by week 12.



Note: Panel A shows point estimates with 50% and 95% credible intervals. Panel B displays subgroup heterogeneity. Panel C illustrates temporal persistence patterns.

Figure 3. Channel Attribution Results with Uncertainty Quantification.

4.2.3. Return on Investment across Marketing Channels

Return on investment analysis extends attribution findings to economic metrics informing budget allocation. Analysis employs fully loaded costs including media placement, creative development, technology subscriptions, sales force compensation, and overhead. Email detailing achieves exceptional ROI through minimal marginal costs with each contact costing pennies compared to prescription value exceeding 3000 dollars annually. Webinar ROI reflects significant upfront investment offset by zero marginal costs for incremental attendees. Sales representative cost structure dominated by personnel compensation creates higher cost per contact approaching 250 dollars constraining ROI. Direct mail suffers from high production costs in 3-8 dollar per piece range. Social media and search marketing exhibit favorable marginal cost structures but face platform limitations. Budget optimization modeling recommends substantial reallocation emphasizing email detailing and webinar expansion. Simulations suggest potential 18-22% improvement in portfolio ROI through optimized allocation while maintaining equity metrics.

4.3. Health Equity Assessment Findings

4.3.1. Stratified Effectiveness across Demographic Groups

Stratified analysis reveals substantial heterogeneity across demographic subgroups. Black non-Hispanic populations demonstrate systematically lower marketing responsiveness compared to White populations across channels with disparities ranging from 2.1 to 4.8 percentage points. Email detailing shows relatively modest racial disparities at 2.1 percentage points. Search marketing exhibits largest disparity at 4.7 percentage points potentially reflecting differential health literacy. Hispanic populations show intermediate effectiveness levels. Rural populations exhibit substantially lower marketing effectiveness at 3.2 percentage points below urban populations with

pronounced gaps for digital channels. Age-stratified analysis identifies distinct patterns. Younger populations aged 18-34 respond most strongly to social media advertising with 9.8% lift compared to 4.2% for patients aged 75 plus. Direct mail effectiveness increases monotonically with age from 4.1% lift for 18-34 year-olds to 11.3% for 75 plus populations.

4.3.2. Identification of Underserved Populations

Systematic analysis identifies demographic segments receiving inadequate marketing reach relative to medical need. Black populations receive 47% lower marketing exposure per capita compared to White populations after adjusting for disease prevalence. Rural populations experience 58% lower per-capita exposure compared to urban areas. Lower socioeconomic quintiles receive 34% less exposure despite higher disease prevalence. Underserved population identification employs multi-dimensional criteria combining low exposure, high disease burden, significant treatment gaps, and documented outcome disparities. Framework flags 87 specific market-demographic combinations meeting criteria representing 12.4% of total volume but 18.7% of disease prevalence. Propensity score-matched comparisons demonstrate 8.3 percentage point improvements in prescription initiation rates and 6.7 percentage point improvements in adherence rates from targeted marketing suggesting meaningful health impact potential.

4.3.3. Budget Allocation Recommendations for Equitable Reach

Framework generates actionable budget allocation recommendations optimizing tradeoffs between commercial objectives and health equity goals. Baseline allocation directs 68% to digital channels, 24% to traditional channels, and 8% to medical education resulting in equity ratio of 2.27. Recommended allocation shifts 12 percentage points from search marketing and social media toward email detailing, direct mail, and webinar investments targeted to underserved segments. Optimized allocation achieves 14% improvement in portfolio ROI while reducing equity ratio to 1.54 through overweighting channels resonant with underserved populations. Direct mail allocation increases by 4 percentage points with geographic targeting prioritizing rural markets. Webinar programming diversifies to include Spanish-language sessions. Implementation roadmap specifies staged rollout beginning with pilot testing in 50 high-priority markets. Continuous monitoring tracks aggregate performance and equity-specific indicators. Adaptive learning protocols enable mid-course corrections.

5. Discussion, Implications, and Conclusion

5.1. Key Findings and Theoretical Contributions

5.1.1. Methodological Advances in Attribution Modeling

Research demonstrates that integrating causal inference principles with conventional marketing attribution substantially enhances accuracy and interpretability. Framework advances methodology through explicit causal modeling using directed acyclic graphs providing transparent assumption representation. Propensity score integration addresses confounding moving beyond correlation toward credible causal interpretation. Bayesian hierarchical structures accommodate complex nested data while providing uncertainty quantification. Equity-aware evaluation represents meaningful extension revealing systematic variation across demographics. Fairness metrics operationalize health equity concepts enabling quantitative assessment. Distributional effectiveness measures characterize heterogeneity comprehensively.

5.1.2. Causal Inference Benefits for Marketing Measurement

Empirical results provide compelling evidence that causal inference integration yields substantial practical benefits. Attribution estimates differ meaningfully from correlational patterns with several channels exhibiting lower effectiveness than unadjusted analyses suggest. Search marketing causal estimates reveal 42% lower impact compared to last-click attribution. Sales representative effectiveness undergoes

downward revision of 31%. Causal framework enables credible extrapolation to alternative allocation scenarios by explicitly modeling counterfactual outcomes. Transparency about causal assumptions strengthens stakeholder confidence. Sensitivity analyses provide balanced perspective on conclusion strength.

5.2. Practical Implications and Policy Alignment

5.2.1. Strategic Guidance for Pharmaceutical Marketers

Research provides actionable strategic recommendations. Email detailing emerges as substantially under-utilized relative to performance potential suggesting meaningful reallocation opportunities. Webinar investments warrant increases particularly for content targeting underserved populations. Search marketing requires reassessment given mediocre causal effectiveness. Channel functions primarily as conversion catalyst rather than awareness-building driver. Direct mail demonstrates advantages for older demographics and rural populations justifying continued investment. Organizational capabilities require evolution to implement equity-aware measurement. Marketing analytics teams need expanded skillsets encompassing causal inference methodologies and fairness metrics. Data infrastructure investments must support demographic integration and subgroup-level reporting.

5.2.2. Compliance with HHS and FDA Health Equity Frameworks

Proposed framework directly addresses federal health agency priorities. Centers for Medicare and Medicaid Services Framework emphasizes expanded demographic data collection and disparity assessment. Framework advances objectives through systematic stratification, explicit equity metric computation, and underserved population identification. Food and Drug Administration emphasis on equitable access extends to promotional activities shaping which populations receive adequate information. Framework's stratified measurement and equity-aware allocation ensure strategies actively reduce rather than exacerbate disparities. Research demonstrates feasibility of incorporating equity considerations at scale. Broader adoption would contribute meaningfully to national equity objectives.

5.2.3. Optimization Strategies for Marketing Resource Allocation

Multi-objective optimization incorporating financial returns and equity constraints enables navigating tensions between commercial imperatives and social responsibility. Framework demonstrates objectives need not conflict with optimized strategies achieving simultaneous improvements. Strategic reallocation emphasizing email and webinar channels improves financial performance while enabling targeted reach expansion. Practical implementation requires establishing explicit equity constraints within optimization formulations. Constraint tightness reflects organizational values. Scenario analysis examines performance across alternative specifications informing executive decision-making. Continuous monitoring ensures recommendations remain appropriate as conditions evolve.

5.3. Limitations, Future Research, and Conclusions

5.3.1. Study Limitations and Boundary Conditions

Several limitations constrain interpretation. Analysis examines single pharmaceutical product within one therapeutic category raising external validity questions. Replication across diverse therapeutic categories would strengthen generalizability confidence. Data limitations including incomplete demographic information, measurement error in exposure metrics, and absence of individual-level identifiers constrain precision. Framework accommodates limitations through uncertainty quantification though residual unmeasured confounding concerns remain. Observational design precludes definitive causal claims despite rigorous methods.

Randomized experiments would provide stronger evidence though practical constraints limit feasibility.

5.3.2. Future Research Directions

Multiple avenues warrant investigation. Incorporation of clinical outcome data would enable assessment of whether effectiveness differences translate into health impact disparities. Individual-level analysis would enhance heterogeneous treatment effect understanding. Machine learning methods could flexibly estimate individual-specific response functions. Behavioral economics insights could inform creative development. Longitudinal analysis examining dynamic response would reveal effectiveness pattern stability. Competitive response modeling would provide complete market dynamics picture. International extensions would illuminate how cultural contexts mediate effectiveness.

5.3.3. Concluding Remarks

Research demonstrates feasibility and value of integrating causal inference with marketing attribution addressing measurement accuracy and health equity challenges. Framework achieves meaningful predictive performance improvements while revealing systematic effectiveness disparities conventional approaches obscure. Methodological advances enable pharmaceutical marketers optimizing resource allocation serving both commercial objectives and equity commitments demonstrating ethical practice and business success need not conflict. Pharmaceutical marketing measurement stands at important juncture as digital transformation expands data availability while heightened scrutiny demands explicit equity attention. Framework provides concrete implementation path for companies advancing beyond aspirational statements toward measurement-driven continuous improvement. Broader adoption would contribute meaningfully to national health equity objectives ensuring essential medical information reaches all populations equitably.

References

1. S. Dingre, V. Girbane, S. Garudkar, P. Todakari, D. Borawake, and M. Deshmukh, "Integrating artificial intelligence in pharmaceutical marketing: Enhancing engagement and efficiency," 2025.
2. A. A. Abayomi, J. C. Ogeawuchi, A. Y. Onifade, O. A. Agboola, R. E. Dosumu, and O. O. George, "Systematic review of marketing attribution techniques for omnichannel customer acquisition models," *International Journal of Advanced Multidisciplinary Research and Studies*, vol. 3, no. 6, pp. 1621-1633, 2023.
3. S. A. Dada, and A. D. Adekola, "Leveraging digital marketing for health behavior change: A model for engaging patients through pharmacies," *International Journal of Science and Technology Research Archive*, vol. 7, no. 2, pp. 050-059, 2024.
4. G. Sabapathy, "Artificial Intelligence in Pharmaceutical Commercial Operations: Transforming Sales Performance and Patient Engagement in the Digital Era," *Journal of Computer Science and Technology Studies*, vol. 7, no. 8, pp. 636-651, 2025.
5. M. F. Ashouri, and M. Tarassoli, "Smart data in healthcare marketing: linking digital transformation to patient behavior and branding," *Social Determinants of Health*, vol. 11, pp. 1-10.
6. O. V. Unanah, and O. J. Mbanugo, "Integration of AI into CRM for effective US healthcare and pharmaceutical marketing," *World Journal of Advanced Research and Reviews*, vol. 25, no. 02, pp. 609-630, 2025.
7. R. Haider, and G. K. Das, "From Promotion to Personalization: The Role of Artificial Intelligence in Pharmaceutical Marketing," *WebLog J Med Sci. wjms. 2025. i2905*, 2025.
8. Z. Dong and F. Zhang, "Deep learning-based noise suppression and feature enhancement algorithm for LED medical imaging applications," *J. Sci., Innov. Soc. Impact*, vol. 1, no. 1, pp. 9–18, 2025.
9. S. Seth, and S. Ramakrishnan, "Innovations in Multi-Touch Attribution Models: Beyond Traditional Marketing Analytics in the Pharmaceutical Sector," In *2025 International Conference on Emerging Smart Computing and Informatics (ESCI)*, March, 2025, pp. 1-5. doi: 10.1109/esci63694.2025.10988316
10. A. Ngamvichaikit, "Leveraging design thinking for pharmaceutical digital marketing," *Asian Journal of Business Research*, vol. 11, no. 1, pp. 120-140, 2021. doi: 10.14707/ajbr.210102
11. T. Anthuvan, K. Maheshwari, and R. Dantu, "Trends in pharmaceutical marketing and branding research: a bibliometric analysis (2009-2023)," *IIM Ranchi Journal of Management Studies*, vol. 4, no. 1, pp. 55-71, 2025. doi: 10.1108/irjms-03-2024-0030
12. J. Zhang, "Deep Learning-Based Attribution Framework for Real-Time Budget Optimization in Cross-Channel Pharmaceutical Advertising: A Comparative Study of Traditional and Digital Channels," In *Proceedings of the 2025 International Conference on Software Engineering and Computer Applications*, June, 2025, pp. 248-254. doi: 10.1145/3747912.3747951

13. X. Ni, Y. Zhang, Y. Pu, M. Wei, and Q. Lou, "A personalized causal inference framework for media effectiveness using hierarchical bayesian market mix models," *Journal of Advanced Computing Systems*, vol. 3, no. 9, pp. 9-23, 2023.
14. Z. Dong and R. Jia, "Adaptive dose optimization algorithm for LED-based photodynamic therapy based on deep reinforcement learning," *J. Sustain., Policy, Pract.*, vol. 1, no. 3, pp. 144–155, 2025.
15. T. J. VanderWeele, and P. Ding, "Sensitivity analysis in observational research: introducing the E-value," *Annals of internal medicine*, vol. 167, no. 4, pp. 268-274, 2017. doi: 10.7326/m16-2607
16. Z. Pan, "AI-Powered Real-Time Effectiveness Assessment Framework for Cross-Channel Pharmaceutical Marketing: Optimizing ROI through Predictive Analytics," In *Proceedings of the 2025 International Conference on Management Science and Computer Engineering*, June, 2025, pp. 220-227. doi: 10.1145/3760023.3760059
17. M. Nankya, A. Mugisa, Y. Usman, A. Upadhyay, and R. Chataut, "Security and privacy in E-health systems: a review of AI and machine learning techniques," *IEEE Access*, 2024. doi: 10.1109/access.2024.3469215
18. Z. Dong, "Adaptive UV-C LED dosage prediction and optimization using neural networks under variable environmental conditions in healthcare settings," *J. Adv. Comput. Syst.*, vol. 4, no. 3, pp. 47–56, 2024.