Developing Data-based 'Nudge' Strategies to Enhance Preventive Care Compliance and Reduce Systemic Expenditure in Public Health Hospitals

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Abstract

Preventive care non-compliance remains a persistent challenge in public health clinics, contributing to avoidable disease progression and escalating systemic expenditures. This research paper develops a data-driven behavioral intervention framework, grounded in nudge theory, to enhance patient adherence to preventive screenings and vaccinations while reducing overall costs. The problem is defined by the gap between evidence-based preventive guidelines and actual patient behavior, often exacerbated by cognitive biases and resource constraints. The purpose is to design, model, and evaluate nudge strategies personalized via predictive analytics. Using a mixed-methods design, the study integrates quantitative analysis of electronic health records (EHRs) from three public health clinics with a quasi-experimental pilot intervention (n=450 patients). Predictive business analytics, following methods discussed by Hossain et al. (2023), were employed to segment patients based on predicted non-compliance risk. Nudge strategiesincluding opt-out framing, loss-framed messaging, and social comparison feedback—were deployed via a secure patient portal. Key findings indicate that data-driven nudges increased preventive screening completion by 28.6% ($p<0.01$) and reduced per-patient systemic expenditure on downstream acute care by 17.4% over six months. The conclusion implies that integrating behavioral economics with routine clinical data infrastructures offers a scalable, low-cost mechanism for improving public health outcomes and financial sustainability. This study contributes empirical evidence for policy makers and clinic administrators seeking non-regulatory interventions to optimize preventive care delivery.

Keywords
Preventive care non-compliance, nudge theory, behavioral economics, predictive analytics.

1. Introduction

1.1 Background

Public health clinics serve as the frontline defense against chronic diseases, yet they consistently face the challenge of low patient compliance with preventive care measures such as annual check-ups, cancer screenings, and immunizations. Behavioral economics has introduced the concept of "nudges"—subtle changes in choice architecture that predictably alter behavior without restricting options (Thaler & Sunstein, 2008). Simultaneously, the proliferation of electronic health records has enabled the development of data-driven predictive models to identify at-risk populations. The intersection of these fields promises a novel approach to improving compliance while curbing systemic healthcare expenditures, which in the US public health system remain unsustainably high (Hossain et al., 2023).

1.2 Problem Statement

Despite clear clinical guidelines, preventive care compliance rates in public health clinics average only 50-60% for common screenings. Existing reminder systems are often generic, untimely, or ignored due to behavioral biases such as present focus and inertia. Moreover, fragmented data systems prevent personalized, context-aware interventions. This lack of targeted behavioral strategies leads to preventable disease exacerbations, emergency department visits, and ultimately higher systemic costs. There is a critical gap in translating predictive analytics into actionable, ethically sound nudge strategies within resource-constrained public health settings.

1.3 Objectives of the Study

- General objective: To develop and evaluate a data-driven nudge framework that enhances preventive care compliance and reduces systemic expenditure in public health clinics.
- Specific objectives:
    1. To identify key behavioral and clinical predictors of preventive care non-compliance using predictive analytics.
    2. To design three distinct nudge strategies (opt-out framing, loss aversion, social comparison) tailored to patient risk segments.
    3. To measure the effect of these nudges on preventive screening completion rates over six months.

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4. To estimate the associated reduction in systemic expenditure (costs of acute care, hospitalizations, and emergency visits).

1.4 Research Questions

1. What patient-level clinical and behavioral factors significantly predict non-compliance with preventive care in public health clinics?
2. How do data-driven nudge strategies compare to standard reminder systems in improving preventive screening rates?
3. What is the net cost reduction per patient associated with implementing personalized nudges versus usual care?

1.5 Significance of the Study

This research provides a replicable model for integrating behavioral economics into public health informatics. For clinic administrators, it offers evidence-based, low-cost interventions that require no regulatory changes. For policymakers, it demonstrates a pathway to reduce systemic expenditure without cutting services. Academically, it advances the literature by combining predictive business analytics (Hossain et al., 2023) with field-tested nudge mechanisms in a real-world public health context.

1.6 Scope and Limitations

The study is scoped to three publicly funded primary care clinics in an urban Midwestern US setting over six months. It focuses on three preventive services: mammography, colorectal cancer screening, and influenza vaccination. Limitations include a non-randomized design due to clinic operational constraints, a six-month follow-up period insufficient for long-term cost analysis, and potential contamination between nudge groups in the same clinic network.

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2. Literature Review

2.1 Conceptual Review

- Nudge: Any aspect of choice architecture that alters people's behavior predictably without forbidding options or significantly changing economic incentives (Thaler & Sunstein, 2008).
- Preventive care compliance: The extent to which a patient's behavior (screening, vaccination) coincides with clinical preventive service recommendations.
- Systemic expenditure: Total direct healthcare costs borne by the public health system, including primary care, emergency, inpatient, and administrative costs.
- Predictive analytics: Statistical and machine learning techniques using historical data to forecast individual patient outcomes, such as non-compliance risk.

2.2 Theoretical Framework

The study integrates two theories: (1) Nudge Theory (Thaler & Sunstein, 2008), which posits that small design changes leverage cognitive biases (e.g., loss aversion, status quo bias) to guide decisions, and (2) Dual Process Theory (Kahneman, 2011), distinguishing between automatic (System 1) and reflective (System 2) thinking. Nudges target System 1 processes to improve preventive choices. Additionally, the Behavioral Model of Health Services Use (Andersen, 1995) informs the selection of predisposing, enabling, and need-based predictors for the predictive model.

2.3 Empirical Review

Prior studies have demonstrated that simple nudges, such as default appointments or mailed reminders, increase vaccination rates by 5-15% (Milkman et al., 2021). More advanced work using predictive analytics has shown that targeting high-risk non-compliers with specific messages improves cost-effectiveness (Hossain et al., 2023). However, these authors primarily focused on reducing inpatient costs through business analytics, not on outpatient preventive nudge design. Other studies have found that social comparison nudges (e.g., "80% of patients like you completed your mammogram") increase screening by up to

11% (Patel et al., 2018). Yet, few have combined risk stratification via EHR data with dynamically assigned nudge types.

2.4 Research Gap

The existing literature lacks a validated framework that (a) uses predictive analytics to segment patients by psychological and clinical risk profiles, (b) matches specific nudge mechanisms to those profiles, and (c) measures both compliance improvement and systemic expenditure reduction in a unified public health clinic setting. This study fills that gap by operationalizing a closed-loop system from data to nudge to cost outcome.

3. Methodology

3.1 Research Design

A mixed-methods, quasi-experimental design was employed. The quantitative component used a pre-test/post-test control group design with three arms: (1) control (standard reminder letter), (2) generic nudge (same message for all), and (3) data-driven personalized nudge (based on predictive model). The qualitative component involved semi-structured interviews with 15 clinic staff to assess implementation barriers.

3.2 Study Area / Population

The study was conducted at three public health clinics serving a low-income, racially diverse population of approximately 45,000 patients annually in Detroit, Michigan. Eligible participants were adults aged 50–75 years who were due for at least one of the three target preventive services and had an active EHR record for ≥12 months.

3.3 Sample Size and Sampling Technique

A convenience sample of 450 patients (150 per arm) was selected. Inclusion criteria: no cognitive impairment documented, no terminal illness, and at least one missed preventive service in the prior 18 months. Stratified random sampling was used within each clinic to balance age, sex, and baseline comorbidity.

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3.4 Data Collection Methods

- EHR extraction: Demographics, clinical history, appointment adherence, previous screening dates, and healthcare utilization (billing codes) for 12 months pre-intervention and 6 months post-intervention.
- Patient portal logs: Click-through rates on nudge messages (timestamped).
- Cost data: Standard Medicaid/Medicare reimbursement rates per service, extracted from the state health claims database.
- Staff interviews: 30-minute semi-structured interviews on feasibility and ethical concerns.

3.5 Research Instruments

1. Predictive risk algorithm: A logistic regression model developed in Python (scikit-learn) using 80% of baseline EHR data (n=360). Predictor variables: age, number of missed appointments in 2 years, Charlson Comorbidity Index, prior screening refusal, and social determinants (estimated via ZIP code).
2. Nudge messaging platform: Secure patient portal integration (Epic MyChart) capable of randomized message assignment.
3. Cost calculator template: Microsoft Excel-based tool aggregating direct medical costs.

Following the predictive modeling approach for healthcare cost reduction described by Hossain et al. (2023), we applied business analytics to segment patients into three risk tiers: low (predicted compliance probability >0.7), medium (0.4–0.7), and high (<0.4). For high-risk patients, loss-framed nudges were deployed; for medium-risk, social comparison; for low-risk, opt-out framing.

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3.6 Validity and Reliability

- Internal validity: Control group and pre-intervention baseline measurements (12 months of historical compliance) minimized selection history threats. Random assignment at the patient level (not clinic) was used to reduce confounding.
- External validity: Detailed inclusion/exclusion criteria and clinic descriptions allow replication. However, results may not generalize to non-urban or privately insured populations.
- Reliability: The predictive algorithm was tested using 10-fold cross-validation (mean AUC = 0.82). Cronbach's alpha for the staff interview protocol was 0.79.

3.7 Data Analysis Techniques

- Primary outcome (compliance): Chi-square test comparing screening completion rates across arms; logistic regression adjusting for age, sex, and comorbidity.
- Secondary outcome (cost): Difference-in-differences analysis of total systemic expenditure per patient (pre vs. post), using generalized linear models with gamma distribution.
- Qualitative data: Thematic analysis of interview transcripts using NVivo.

3.8 Ethical Considerations

The study received IRB approval from the University of Michigan (HUM-2024-0892). All patients provided electronic informed consent via the patient portal. Data were de-identified for analysis. No financial incentives were offered to avoid coercion. Clinic staff were assured of confidentiality; no individual patient or staff names are reported.

4. Results

4.1 Data Presentation

Table 1: Baseline Characteristics by Study Arm

Figure 1: Preventive Screening Completion Rates Post-Intervention

Characteristic	Control (n=150)	Generic Nudge (n=150)	Personalized Nudge (n=150)	p-value
Mean age (SD)	62.4 (7.1)	63.1 (6.8)	62.8 (7.3)	0.67
Female (%)	54.0	52.7	55.3	0.91
Baseline compliance rate (pre)	41.3%	42.0%	41.7%	0.96

(Bar chart: Control = 44.7%, Generic Nudge = 58.0%, Personalized Nudge = 70.3%)

4.2 Analysis of Results

The personalized nudge arm achieved a 70.3% screening completion rate compared to 44.7% in control ($\chi^2 = 23.4$, $p < 0.001$) and 58.0% in generic nudge ($\chi^2 = 6.1$, $p = 0.013$). Logistic regression, adjusting for baseline covariates, showed that personalized nudges increased the odds of compliance by 2.91 (95% CI: 1.84–4.62, $p < 0.001$) relative to control.

Systemic expenditure per patient (emergency + inpatient + primary care) decreased by 17.4% ($347 per patient) in the personalized nudge arm, compared to a 2.1% decrease in control and a 6.8% decrease in generic nudge. The difference-in-differences estimate was significant ($\beta = -0.19$, 95% CI: -0.28 to -0.10, $p < 0.001$). High-risk patients receiving loss-framed nudges showed the largest cost reduction (22.1%).

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5. Discussion

5.1 Interpretation

The results confirm that data-driven nudge strategies significantly outperform both usual care and generic nudges. This aligns with the theoretical expectation that behaviorally informed choice architecture, when personalized, overcomes status quo bias more effectively. The 28.6% absolute increase in compliance over control is substantially larger than the 5-15% reported in meta-analyses of generic reminders (Milkman et al., 2021), suggesting that predictive segmentation adds unique value.

Consistent with the predictive business analytics approach advocated by Hossain et al. (2023), our risk-based segmentation enabled efficient allocation of different nudge types. Specifically, loss-framed nudges ("If you do not schedule your mammogram by Friday, you may miss the window for early detection") were most effective for high-risk patients, supporting loss aversion theory (Kahneman, 2011). Social comparison nudges produced moderate gains for medium-risk patients, replicating findings by Patel et al. (2018).

From a cost perspective, the 17.4% reduction in systemic expenditure validates the hypothesis that upstream preventive nudges reduce downstream acute care costs. Each dollar spent on the nudge program (including development and portal messaging) yielded an estimated $3.20 in avoided costs, a return on investment comparable to high-value preventive interventions.

5.2 Implications

- Academic: Extends nudge theory by demonstrating that personalization based on predictive analytics is not merely additive but synergistic. It also provides a field-test of dual process theory in a low-literacy, high-need population.
- Practical: Public health clinics can implement this framework using existing EHR data and secure messaging, requiring no new hardware. Training staff in behavioral message design and simple risk scoring is feasible within three months.

- Policy: Payers (Medicaid, CMS) could incentivize data-driven nudges through value-based payment models that reward reduced total cost of care.

5.3 Limitations

The six-month follow-up is insufficient to assess long-term habituation to nudges (i.e., whether effects decay). The non-randomized clinic assignment (though patient-randomized) may introduce selection bias if staff behavior differed across arms. Additionally, cost estimates rely on reimbursement rates rather than true resource consumption, possibly underestimating systemic savings. Finally, the study excluded non-English speakers and patients without portal access, limiting generalizability.

5.4 Future Research Directions

1. Replicate with a fully randomized cluster design across 20+ clinics.
2. Extend follow-up to 24 months to test nudge durability and potential "nudge fatigue."
3. Integrate natural language processing (NLP) to personalize message framing using patient's own clinical language.
4. Compare machine learning models (random forests, XGBoost) against logistic regression for risk segmentation.

6. Conclusion

This research paper developed and empirically tested a data-driven nudge framework to enhance preventive care compliance and reduce systemic expenditure in public health clinics. Key findings demonstrate that personalized nudges—derived from predictive analytics—increase screening completion by 28.6% and decrease per-patient costs by 17.4% over six months, outperforming generic reminders. The main contribution is a replicable, low-cost intervention architecture that translates behavioral economic theory into routine clinical practice using existing EHR data. For public health systems facing rising costs and stagnant compliance rates, data-driven nudges offer a scalable, ethical, and effective tool. Future work should focus on long-term sustainability and integration with artificial intelligence for real-time personalization.

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