Forecasting Disease Progression to Prevent High-Cost Acute Episodes in Vulnerable Medicare Advantage Populations

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Abstract

Rising healthcare expenditures in Medicare Advantage (MA) populations are disproportionately driven by high-cost acute episodes (HCAEs) among vulnerable subgroups with multiple chronic conditions. Traditional reactive care models fail to anticipate disease progression, leading to preventable hospitalizations and emergency department overuse. This study addresses the gap in predictive analytics tailored specifically to clinically vulnerable MA enrollees by developing and evaluating a machine learning-based forecasting framework for HCAEs. Using a retrospective cohort design, we analyzed five years of electronic health records and claims data (N = 45,000) from a large MA plan serving a socioeconomically diverse region. The primary methodology integrated gradient boosting machines (XGBoost) with time-varying risk markers to forecast 30-day HCAE risk. Key findings demonstrate that our model achieved an area under the curve (AUC) of 0.89 (95% CI: 0.87–0.91), outperforming traditional risk adjustment methods. Most influential predictors included labile biomarker trajectories, recent acute care utilization, and social determinants of health. Implications suggest that embedding such forecasts into clinical workflows could reduce avoidable HCAEs by up to 34%, lowering per-member-per-month costs while improving health equity. This research contributes a validated predictive framework for proactive, precision-oriented population health management.

Keywords
Medicare Advantage, High-cost acute episodes, Predictive analytics, Population health management.

1. Introduction

1.1 Background

Medicare Advantage (MA) plans now cover over half of all Medicare beneficiaries, including a rapidly growing segment of individuals with complex, multimorbid conditions (Liberty et al., 2022). Within this population, a small proportion—approximately 15%—

accounts for nearly 80% of total healthcare spending, largely driven by high-cost acute episodes (HCAEs) such as septic shock, acute heart failure decompensation, and hyperglycemic crises (Wallace et al., 2021). Vulnerable MA subgroups—including racial and ethnic minorities, dual-eligible beneficiaries, and those with housing instability—experience HCAEs at significantly higher rates due to fragmented care access, low health literacy, and unaddressed social needs (Nguyen & Smith, 2020). The inability to forecast disease progression accurately in real time perpetuates a reactive cycle: providers intervene only after clinical deterioration, incurring substantial avoidable costs and suffering.

1.2 Problem Statement

Current risk stratification methods used by MA plans, such as hierarchical condition categories (HCCs) and retrospective claims-based algorithms, are fundamentally limited for preventing HCAEs. These tools rely on static, annual diagnoses and do not capture dynamic deterioration trajectories (e.g., worsening renal function, glycemic variability) or social contextual factors that precipitate acute events (Chen et al., 2022). Consequently, high-risk patients often experience preventable hospitalizations that could have been averted with timely ambulatory intervention. A critical gap exists: no validated forecasting system has been designed specifically for vulnerable MA populations that integrates clinical time series, utilization patterns, and social determinants into an actionable, episode-prevention framework.

1.3 Objectives of the Study

General objective: To develop and validate a predictive forecasting model that identifies vulnerable Medicare Advantage beneficiaries at imminent risk of a high-cost acute episode, enabling targeted preemptive intervention.

Specific objectives:

1. To construct a longitudinal cohort of MA enrollees with multiple chronic conditions and extract predictors from EHRs, claims, and social risk data.

2. To train and internally validate a machine learning model (XGBoost) for 30-day HCAE risk prediction.
3. To compare model performance against traditional HCC-based risk scores.
4. To identify the most influential time-varying and static predictors of HCAEs.
5. To simulate the potential cost impact of deploying the model within a proactive care management pathway.

1.4 Research Questions

RQ1: To what extent can a machine learning model using dynamic clinical and social predictors forecast 30-day high-cost acute episodes in vulnerable Medicare Advantage populations, compared to traditional risk adjustment methods?

RQ2: Which specific time-varying biomarkers and social determinants of health most strongly predict near-term HCAEs?

RQ3: What is the estimated reduction in per-member-per-month acute care costs if the model's predictions are used to trigger protocolized preventive interventions?

1.5 Significance of the Study

This research provides a practical, empirically grounded tool to shift MA population health from reactive to predictive. For health plans, accurate HCAE forecasting enables value-based interventions (e.g., transitional care teams, telehealth monitoring, in-home medication reconciliation) precisely when they yield the highest marginal benefit. For clinicians, episode prediction supports caseload prioritization and proactive titration of chronic disease management. For vulnerable patients, reducing avoidable acute episodes directly improves quality of life, reduces functional decline, and mitigates medical debt. Furthermore, the study addresses health equity by explicitly modeling social determinants as modifiable risk factors.

1.6 Scope and Limitations

The study is scoped to a single large MA plan serving an urban and semi-rural region in the Midwest United States, with data from January 2018 to December 2022. The vulnerable population is defined as adults aged ≥65 years with ≥2 chronic conditions from a specified list (diabetes, heart failure, CKD, COPD, or depression) and at least one social risk indicator (low-income subsidy, area deprivation index ≥75th percentile, or prior-year emergency department visit for ambulatory care-sensitive condition). Limitations include possible selection bias (only patients with complete data linkages), unmeasured confounding (e.g., detailed caregiver support), and the retrospective design, which precludes causal inference about intervention effects.

2. Literature Review

2.1 Conceptual Review

High-cost acute episode (HCAE): An inpatient admission or observation stay resulting in total episode payments exceeding the 90th percentile for the MA population, typically driven by conditions like acute respiratory failure, severe sepsis, major cardiovascular events, or metabolic decompensation (Wallace et al., 2021). Vulnerable population: In MA, beneficiaries who are dually eligible for Medicaid, have a social frailty index above a threshold, or reside in historically marginalized communities (Nguyen & Smith, 2020). Disease progression forecasting: The use of longitudinal data to estimate the probability of transition from a stable chronic state to an acute decompensation state within a defined temporal window.

2.2 Theoretical Framework

This study integrates two complementary theories. First, the Chronic Care Model (CCM) posits that productive interactions between informed, activated patients and prepared, proactive teams reduce acute complications (Wagner et al., 2001). Forecasting extends CCM by enabling preemptive team activation before patient-perceived deterioration. Second, the Behavioral Model for Vulnerable Populations (Gelberg et al., 2000) emphasizes that

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predisposing, enabling, and need factors—including social instability—interact to shape healthcare utilization. Our model operationalizes these domains as time-varying predictors.

2.3 Empirical Review

Several studies have explored predictive analytics for acute care use. Hossain, ataur Rahman, Zerine, Islam, Hasan, and Doha (2023) demonstrated that predictive business analytics applied across US public health systems reduced healthcare costs by improving resource allocation, though their work did not focus specifically on Medicare Advantage or on forecasting acute episodes from dynamic disease trajectories. Chen et al. (2022) developed a deep learning model for 90-day readmission in Medicare fee-for-service, achieving an AUC of 0.79, but excluded social determinants and did not target HCAEs specifically. Liberty et al. (2022) reported that MA plans using advanced analytics reduced hospitalizations by 12%, yet their model was not publicly validated. Nguyen and Smith (2020) showed that social risk factors independently predict acute events, but no study has integrated these with high-frequency biomarkers in a vulnerable MA cohort. Wallace et al. (2021) identified cost drivers but did not produce a prospective forecasting tool.

2.4 Research Gap

No existing study has developed and internally validated a machine learning model for 30-day HCAE prediction that simultaneously incorporates (a) dynamic lab and vital sign trajectories, (b) recent acute care utilization patterns, (c) claims-based medication refill adherence, and (d) individual-level social determinants. Furthermore, prior work has not compared such a model against the operational benchmark of HCC risk scores within an MA population explicitly defined by vulnerability. This study fills that gap.

3. Methodology

3.1 Research Design

A retrospective cohort study with a predictive modeling design was employed. The unit of analysis was the patient-month (each month, starting 12 months after enrollment, with outcome assessed in the subsequent 30 days). The design is quantitative and prognostic.

3.2 Study Area and Population

Data were obtained from a not-for-profit MA plan serving 12 counties in the Midwest (total MA enrollment ≈ 210,000). The study population included all beneficiaries aged ≥65 years, continuously enrolled for ≥18 months, with at least two chronic conditions from the prespecified list and at least one social risk indicator. The final cohort comprised 45,000 unique beneficiaries.

3.3 Sample Size and Sampling Technique

The full eligible cohort was included (no sampling). With 45,000 beneficiaries contributing an average of 24 patient-months each, the analytic dataset contained 1,080,000 patient-month observations, providing ample power for machine learning with sparse events.

3.4 Data Collection Methods

Secondary data were extracted from three sources: (1) electronic health records (EHRs) from associated health systems (vital signs, labs, encounter diagnoses), (2) Medicare Advantage claims (inpatient, outpatient, pharmacy), and (3) plan-based social risk flags (low-income subsidy, dual eligibility, zip-code-level Area Deprivation Index). Data were linked via a unique de-identified patient identifier. Following the approach of Hossain et al. (2023), predictive analytics pipelines were designed to harmonize structured clinical data from disparate source systems into a unified analytical file, ensuring temporal alignment of predictors with outcome windows.

3.5 Research Instruments

The primary instrument was a custom predictive modeling pipeline implemented in Python 3.10 using the XGBoost library (version 1.7). Feature engineering tools included tsfresh for time-series feature extraction and a medicaid gap indicator derived from pharmacy claims. The outcome label (HCAE) was defined as an inpatient admission with total episode cost > $15,000 or any ICU admission exceeding 48 hours, occurring within 30 days of the prediction date.

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3.6 Validity and Reliability

Predictive validity was assessed via temporal validation: training on months 1–36, tuning on months 37–42, and testing on months 43–60 (temporal hold-out). Reliability of predictor extraction was ensured through double-programmed extraction scripts with 5% audit. The HCC risk score (reference benchmark) was computed using the CMS-HCC V24 model for comparability.

3.7 Data Analysis Techniques

Missing data (≤7% per predictor) were handled using multivariate imputation by chained equations. The primary analysis trained an XGBoost classifier with hyperparameter tuning using Bayesian optimization (AUC as objective). Performance was evaluated using AUC, sensitivity at fixed specificity (0.80), and calibration slope. Variable importance was assessed via SHAP (SHapley Additive exPlanations) values. Cost impact simulation used a decision curve analysis framework, assuming a hypothetical care management intervention costing $500 per targeted patient-month and preventing 30% of predicted HCAEs.

3.8 Ethical Considerations

The study received approval from the Institutional Review Board (IRB #2023-0891) with a waiver of informed consent due to retrospective design and use of de-identified data. A data use agreement was executed with the MA plan. All patient identifiers were removed, and a limited dataset was stored on an encrypted server.

4. Results

4.1 Data Presentation

The cohort (N=45,000) was 58% female, mean age 74.3 years (SD 7.1), 34% dual-eligible, 22% non-Hispanic Black, and 18% Hispanic. Over the 5-year study period, 11,610 HCAEs occurred in 8,100 unique patients (18% of cohort), with an overall density of 0.012 events per patient-month. Table 1 presents baseline characteristics by HCAE status. Figure 1 (line plot) shows that the weekly moving average of labile blood pressure and glucose variability rose significantly 14 days before an HCAE.

Table 1. Baseline Characteristics of the Study Cohort

Characteristic	No HCAE (n=36,900)	HCAE (n=8,100)	p-value
Age (mean, SD)	74.0 (7.0)	75.6 (7.4)	<0.001
Dual eligible	31%	48%	<0.001
Diabetes + CKD	22%	41%	<0.001
Prior ED visit (90 days)	14%	53%	<0.001

4.2 Analysis of Results

The XGBoost model achieved a test-set AUC of 0.89 (95% CI: 0.87–0.91), compared to 0.68 for the HCC risk score (p<0.001). At 80% specificity, sensitivity was 0.73 (positive predictive value 0.26). Calibration slope was 0.94, indicating good agreement. The most influential features (SHAP value) were: (1) 14-day variability in estimated glomerular filtration rate (eGFR), (2) a composite labile blood pressure index, (3) a 7-day count of ambulatory care-sensitive condition-related outpatient visits, (4) medication refill gap >30%, and (5) dual eligibility status. Social determinants (area deprivation index, living alone proxy) added 0.04 to baseline AUC. Feature interaction analysis revealed that the combination of labile eGFR and recent emergency department visit conferred a 6.2x increased odds of HCAE within 30 days.

5. Discussion

5.1 Interpretation

RQ1 is answered affirmatively: the XGBoost model substantially outperformed traditional risk adjustment (AUC 0.89 vs. 0.68), demonstrating that dynamic, time-varying predictors (especially trajectory-based biomarkers) are critical for near-term HCAE forecasting. For

RQ2, labile kidney function and blood pressure variability were dominant, suggesting that physiologic instability precedes clinical events by 1–3 weeks—a window for action. RQ3 simulation found that targeting the top 10% of predicted risk each month could prevent an estimated 34% of HCAEs (95% simulation interval: 28–39%), reducing PMPM acute costs by 147(*from*432 to $285). These findings align with Hossain et al. (2023), who noted that predictive business analytics across public health systems reduced overall costs by enabling proactive resource reallocation; our extension shows that episode-specific forecasting in vulnerable MA populations yields an even larger marginal return. Unlike earlier models (Chen et al., 2022; Liberty et al., 2022), our approach integrates social risk features quantitatively and produces actionable lead time.

5.2 Implications

Academic implications: The study introduces and validates the concept of "dynamic vulnerability signatures"—combinations of biomarker instability, recent utilization, and social risk that precede HCAEs. Future forecasting models should move from static risk scores to time-series embeddings. Practical implications: MA plans can deploy the XGBoost model within their care management platforms. For patients flagged with >0.20 predicted risk, a protocolized intervention (e.g., nurse-led medication titration, daily remote monitoring, social work outreach) could be triggered. This aligns with the Chronic Care Model's proactive team principle and addresses health equity by explicitly acting on dual-eligibility and residential instability flags.

5.3 Limitations

Retrospective design may introduce temporal bias (predictors and outcomes measured within same records). The single-region sample limits generalizability to other geographic and MA contract types. Our HCAE definition (cost+ICU threshold) may miss costly episodes without ICU stays (e.g., some cancer admissions). Unmeasured confounders include cognitive status, informal caregiver availability, and detailed nutrition data. Additionally, the simulated cost impact assumes intervention efficacy from prior studies; a prospective randomized trial is needed for causal cost-effectiveness estimates.

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5.4 Future Research Directions

Prospective validation of the model in a stepped-wedge cluster trial should be conducted across multiple MA plans. Augmenting the model with natural language processing of clinical notes (e.g., social work assessments, functional status) may further improve performance. Finally, developing an interpretable, lightweight version for deployment in community health centers serving vulnerable populations would enhance translational impact.

6. Conclusion

This research developed and internally validated a forecasting framework for high-cost acute episodes among vulnerable Medicare Advantage beneficiaries. Using XGBoost with dynamic clinical and social predictors, the model achieved excellent discrimination (AUC 0.89) and identified actionable lead times of 1–3 weeks. Key contributions include: (1) the first HCAE prediction model tailored to vulnerable MA populations, (2) empirical ranking of time-varying predictors (labile eGFR, blood pressure variability, recent utilization, medication gaps, and dual eligibility), and (3) a simulation showing potential 34% reduction in acute costs. For MA plans, transitioning from static HCC scores to dynamic forecasting is a feasible and high-value step toward equitable, proactive population health. As healthcare systems increasingly bear risk for outcomes, forecasting disease progression becomes not merely a technical exercise but a moral imperative for protecting the most vulnerable.

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