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Longitudinal Cohort Intelligence for Self-Insured Employer Groups: A Predictive Framework for Healthcare Cost Trajectory Modeling and Proactive Risk Intervention

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The structural asymmetry in the management of healthcare costs faced by self-insured employer groups is that it is experienced in the short run, and accumulating over months and years are the clinical and behavioral risk factors that drive them. The traditional employer health analytics models are not sufficient to manage this asymmetry, based on annual claims summaries and only after cost events have occurred reactive identification of high-cost claimants. In the current paper, the author presents the Employer Group Cohort Intelligence Framework (EGCIF) as a longitudinal predictive analytics model, which models the individual member cost trends within rolling observation windows, and thus allows cost inflection points to be identified in advance before claims spending materializes. EGCIF proposes four analytical components, including a temporal cohort segmentation model which stratifies the members of the employer groups in terms of their cost trajectory class rather than a point-in-time risk score; a cost inflection-detection algorithm that identifies the members of the employer groups who are currently on a cost trajectory which is either stable or accelerating; a population-level cost-concentration index which estimates the proportion of the projected cost growth which is attributable to a clinically addressable sub-population; and an intervention timing optimization model which prioritizes the care management resources in terms of the expected cost reduction payoff subject to capacity constraint. The operationalization of the EGCIF performance entails the four formally defined measures: the Trajectory Prediction Accuracy (TPA), Cost Inflection Lead Time (CILT), Population Addressability Index (PAI), and Intervention Return on Engagement (IRE). Analysis of 14 synthetic cohorts of employer groups numbering 187,400 member-years has demonstrated that the identification of the high-cost event by the EGCIF trajectory-based identification is 34.7% earlier than conventional annual risk stratification, and its average Cost Inflection Lead Time is 94.2 days. The best resource allocation result logically under EGCIF trajectory-informed intervention prioritization (IRER) is 2.41x, which represents USD 2.41 of the healthcare costs avoided by the intervention, divided by USD 1.00 of the care management expenditure, which is a standard risk-score-based approach typically used in care management. The findings advance enterprise healthcare analytics from retrospective reporting to longitudinal predictive intelligence, with direct application to self-insured employer group cost governance.

Keywords: Healthcare cost modeling, employer group analytics, longitudinal cohort analysis, predictive risk stratification, self-insured employers, cost trajectory modeling, proactive intervention, enterprise decision support systems.

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I. Introduction

Self-insured employer groups are the largest and most analytically significant sector of the US employer benefits market in that the groups bear direct financial responsibility concerning the healthcare costs of their employee groups but do not transfer risk to an insurance company. About 65 percent of the US workers who are provided with employer-sponsored medical care are enrolled in self-insured plans and the direct costs are the over USD 800 billion in annual healthcare spending directly borne by employers [1]. Healthcare expenses constitute the second-largest operating expense (albeit, after compensation) to large employers and cost trajectory management is a strategic financial necessity rather than an HR administrative operation.

Information systems wise this cost management issue is essentially an enterprise decision intelligence architecture issue. The analytical infrastructure that is typically deployed on most of the self-insured benefit administration platforms of employers that offer benefit plans, such as annual claims summaries, point-in-time risk scoring, and retrospective identification of high cost claimants, represents a type of reactive reporting systems and not a type of proactive decision support infrastructure. The presented Employer Group Cohort Intelligence Framework (EGCIF) in the current paper reconceptualizes the governance of employer healthcare costs as a longitudinal predictive intelligence system: an organized analytical architecture that packages a trajectory modeling, change-point detection, population addressability quantification, and intervention optimization together into a decision-grade enterprise information system deployable within the current benefits administration and business intelligence platform environments. This framing places EGCIF in the literature on enterprise decision support systems and extends it to the temporal and clinical peculiarities of the healthcare cost dynamics of self-insured employers.

The main issue of health cost management in employer groups is temporal: the clinical and behavioral risk factors which will cause high-cost claims over the next year exist today and are observable, but are not identified by traditional analytics models. The prevailing paradigm in employer health analytics is retrospective claims analysis: at the conclusion of a plan year, total claims spending is summed by cost type, high-cost claimants are identified, and care management outreach is directed at those who have already incurred significant expenditure. This is not merely a suboptimal paradigm it is a structural inversion. By the time a member appears on a high-cost claimant list, the cost event that produced the claim has already occurred. Intervention at this point may reduce future expenditure but cannot recover costs already incurred.

The alternative proactive detection of members whose cost trajectory is bending toward a high-cost position before cost realization requires an entirely different analytical architecture. Rather than examining the distribution of historical claims, it requires modeling the longitudinal pattern of individual member risk over time: at what point does a member's utilization pattern, chronic condition progression, or behavioral risk indicators signal a transition from stable to accelerating utilization? This is the problem the Employer Group Cohort Intelligence Framework (EGCIF) is designed to solve.

EGCIF distinguishes itself from existing population health management and predictive risk stratification approaches in three ways. First, it operates on rolling longitudinal observation windows rather than annual cross-sections, enabling detection of trajectory changes rather than identification of current risk levels. Second, it models cost trajectories at the cohort class level, recognizing that individual members follow recognizable trajectory patterns shared across populations enabling more stable prediction than individual-level models

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trained on sparse claims histories. Third, it explicitly models the intervention timing optimization problem: given limited care management capacity, which members should be prioritized for outreach, and at what point in their trajectory does intervention produce maximum cost reduction return?

A key empirical finding of this paper is that EGCIF-optimized intervention assignment achieves an IRE of 2.41x more than 74% higher than random selection and 27% higher than highest-risk-score prioritization confirming that trajectory-class modeling provides actionable advantage over conventional risk stratification approaches not only in detection timing but in intervention resource allocation efficiency.

A. Research Questions

EGCIF addresses four research questions: (RQ1) How can individual member healthcare cost trajectories be modeled longitudinally to enable detection of cost inflection points before expense realization? (RQ2) What cohort segmentation approach maximizes the stability and predictive validity of trajectory class assignments for self-insured employer group populations? (RQ3) How can employer group cost concentration be measured and used to identify the addressable sub-population that drives disproportionate cost growth? (RQ4) How should proactive intervention resources be allocated across identified high-trajectory members to maximize cost reduction return subject to capacity constraints?

B. Principal Contributions

- A longitudinal cohort segmentation methodology that classifies employer group members into cost trajectory classes using rolling 12-month observation windows with 3-month update cycles, producing more stable and actionable risk stratification than annual point-in-time scoring.
- A cost inflection detection algorithm combining change-point analysis with trajectory class transition modeling to identify members whose cost trajectory is accelerating 60 to 180 days before high-cost event realization.
- A Population Addressability Index (PAI) that quantifies the proportion of employer group cost growth concentrated in a clinically and behaviorally addressable sub-population, providing a measurable upper bound on proactive intervention impact.
- An intervention timing optimization model formulated as a constrained resource allocation problem, enabling care management teams to maximize cost reduction return subject to staffing and outreach capacity constraints.
- Four formally defined metrics (TPA, CILT, PAI, IRE) providing quantitative governance of EGCIF prediction and intervention performance across employer group deployments.

II. Related Work

A. Population Health Management and Risk Stratification

The conceptual framework of proactive healthcare cost governance within employer group settings has been established by population health management (PHM). Kindig and Stoddart [2] define population health as the health outcomes of a defined group of people, including the distribution of such outcomes within the group, establishing the population-level analytical perspective on which EGCIF is based. Jencks, Williams, and Coleman [3] document the high rate of preventable hospital readmission as a major contributor to avoidable high-cost claims in self-insured groups, identifying early intervention as the primary mechanism for cost reduction. The Disease Management Association of America [4] reports that structured disease management programs in identified high-risk

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populations generate cost reduction ratios of 2:1 to 4:1 relative to intervention cost ratios that the IRE metric of EGCIF is designed to measure prospectively rather than retrospectively.

Predictive risk stratification, the application of statistical models to assign prospective risk scores to individual members has come to dominate intervention candidate identification in commercial population health management platforms. Fleishman and Cohen [5] provide a comprehensive analysis of prospective risk stratification models, finding that concurrent models based on current-year claims significantly outperform prospective models, particularly for members in cost-trajectory transition. This observation directly motivates EGCIF's trajectory-class approach: by modeling trajectory transitions rather than point-in-time risk scores, EGCIF addresses the prospective prediction gap identified by Fleishman and Cohen. Pope et al. [6] introduce the Hierarchical Condition Categories (HCC) model for prospective cost prediction, demonstrating that chronic condition burden outperforms prior-year spending as a predictor of subsequent-year expenditure — a finding that EGCIF applies in trajectory feature engineering through condition progression modeling.

B. Longitudinal Health Data Modeling

Longitudinal modeling of individual health trajectories has been developed primarily in clinical epidemiology and health services research rather than enterprise analytics contexts. Jones [7] introduces group-based trajectory modeling (GBTM) as a method for identifying distinct longitudinal trajectories within heterogeneous populations, demonstrating application to health behavior and clinical outcome data. GBTM's core insight that population heterogeneity in outcomes reflects a mixture of distinct trajectory classes rather than a continuous distribution around a single mean is directly adopted in EGCIF's cohort segmentation methodology. Nagin [8] provides the comprehensive methodological treatment of GBTM, including the finite mixture model specification and maximum likelihood estimation procedures underlying EGCIF's trajectory class assignment algorithm. Charlson et al. [9] develop the Charlson Comorbidity Index as a summary measure of chronic condition burden, providing the condition-weighting scheme incorporated into EGCIF's trajectory feature construction.

Change-point detection the identification of the time point at which a statistical process undergoes a structural change provides the methodological foundation for EGCIF's cost inflection detection algorithm. Page [10] introduces the CUSUM (Cumulative Sum) control chart as a sequential detection procedure for identifying changes in process mean, directly applicable to individual member utilization trajectory monitoring. Killick and Eckley [11] develop the PELT (Pruned Exact Linear Time) algorithm for efficient multiple change-point detection in time series data, enabling cost inflection detection across large employer group member populations at computation costs compatible with quarterly analytics cycles.

C. Healthcare Cost Prediction in Employer Benefit Contexts

Employer-specific healthcare cost prediction has received less systematic academic attention than clinical prediction modeling, despite the scale of self-insured employer healthcare expenditure. Druss et al. [12] document the high concentration of healthcare costs in employer group populations the top 1% of claimants typically account for 20–25% of total costs, and the top 5% account for 50–55% establishing the cost concentration phenomenon that EGCIF's PAI metric formalizes. Bhattarai et al. [13] examine the stability of high-cost claimant status across years, finding that only 40–50% of top-decile claimants in year one remain in the top decile in year two, motivating trajectory-based rather than static high-cost identification. Silow-Carroll, Edwards, and Lashbrook [14] examine employer strategies for healthcare cost management, identifying predictive analytics as the highest-impact intervention but noting the absence of standardized frameworks for trajectory-based risk identification.

D. Intervention Optimization in Population Health

Resource allocation for proactive health interventions has been studied in public health and operations research contexts. Brandeau, Sainfort, and Pierskalla [15] provide a comprehensive treatment of operations research methods in healthcare, including constrained optimization models for population-level intervention allocation. Meltzer [16] develops the threshold analysis approach for healthcare intervention prioritization, establishing that cost-effective intervention allocation requires modeling the marginal cost reduction return of each intervention candidate rather than ranking by risk score alone. The IRE metric in EGCIF operationalizes this marginal return perspective within enterprise care management workflows, enabling prioritization by expected cost reduction per intervention unit rather than by trajectory risk score.

III. The Employer Group Cohort Intelligence Framework (EGCIF)

A. Formal Notation and Scope

Let $M = \{m_1,\ldots,m_n\}$ represent the population of members within an employer group observed over a time horizon $T = \{t_1,\ldots,t_K\}$, defined at monthly intervals. For each member m_i at time t_k, we define: $x_{ik} \in \mathbb{R}^p$ as a feature vector capturing claims utilization, chronic disease indicators, pharmacy usage, care gap status, and demographic risk factors; $c_{ik} \in \{1,\ldots,C\}$ as the assigned trajectory class; and $y_{ik} \in \mathbb{R}^+$ as the total healthcare expenditure over the subsequent 90-day window. A binary indicator $\delta_{ik} \in \{0,1\}$ flags whether member m_i is transitioning toward a higher-cost trajectory at time t_k. The intervention candidate pool at time t, denoted $I_t \subseteq M$, includes all members for whom $\delta_{ik} = 1$, subject to a capacity constraint $|I_t| \leq K_{max}$.

B. Component 1: Longitudinal Trajectory Segmentation

The framework partitions members into C trajectory classes using group-based trajectory modeling applied to rolling 12-month observation windows, refreshed quarterly. Class assignment is determined by maximizing the posterior probability of membership given observed longitudinal data:

$$c_{ik} = \text{argmax}_j\ P(\text{Class} = j \mid x_{i,t-11:t}) = \text{argmax}_j \left[\pi_j \cdot \prod_{s=t-11}^{t} f_j(x_{is})\right]$$

where π_j denotes the prior probability of class j, and $f_j(x_{is})$ is the class-conditional likelihood of the feature vector under class j.

Operationally, six trajectory classes (C = 6) provide sufficient interpretability:

1. Stable-Low: persistently low utilization, no disease progression.
2. Stable-Moderate: controlled chronic conditions with predictable utilization.
3. Stable-High: high-cost conditions under stable management.
4. Accelerating-Moderate: moderate baseline with emerging upward cost trends.
5. Accelerating-High: rapidly escalating utilization with multi-condition burden.
6. Acute-Event: episodic high-cost events without sustained trajectory.

Classes 4 and 5 constitute the primary targets for intervention.

Class number selection: GBTM models were estimated for C = 3 through C = 8 trajectory classes across the 14 synthetic employer group cohorts. Model selection followed the Bayesian Information Criterion (BIC), with lower BIC values indicating preferred solutions.

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BIC improved consistently from C = 3 (−14,842) through C = 6 (−11,203) and reached a plateau at C = 7 (−11,189), indicating that additional classes beyond six did not provide meaningful improvement in model fit relative to the added complexity. The C = 6 solution was further evaluated for assignment quality: mean posterior probability of assigned class membership was 0.84 (range: 0.79–0.91 across classes), exceeding the 0.70 minimum threshold recommended by Nagin [8] for interpretable class assignment. The six identified classes provided clinically and operationally meaningful stratification validated against expert review of representative member trajectories in each class.

C. Component 2: Cost Inflection Detection

Inflection detection identifies members transitioning from stable to accelerating cost trajectories using a hybrid cumulative sum (CUSUM) and transition probability approach. Define the residual series:

$$r_{ik} = y_{ik} - \hat{y}_{ik}$$

where $\hat{y}_{ik}$ is the expected expenditure based on the assigned trajectory class. The CUSUM statistic is then computed as:

$$S_{ik} = \max(0, S_{i,k-1} + r_{ik} - \kappa_j)$$

Here, κ_j is a class-specific slack parameter calibrated to residual variance. An inflection signal is triggered when $S_{ik} > h_j$, where h_j is a threshold tuned to maintain false positive rates below 8% for stable classes (1–3) and below 12% for accelerating classes (4–5). To enhance predictive power, the CUSUM signal is supplemented with a forward-looking transition probability:

$$T_{ij}(t) = P(c_{i,t+1} = j \mid c_{it}, x_{it})$$

This hybrid formulation integrates retrospective deviation detection with prospective trajectory risk estimation.

D. Component 3: Population Addressability Index (PAI)

The Population Addressability Index (PAI) measures the share of projected cost growth attributable to members whose conditions are both high-impact and clinically modifiable:

$$PAI = \sum_{i \in A_t} \Delta C_i(t) \,/\, \sum_{i \in M} \Delta C_i(t)$$

where $A_t \subseteq M$ includes members flagged for inflection ($\delta_{ik} = 1$) and for whom validated intervention pathways exist. $\Delta C_i(t)$ represents the projected 12-month incremental cost.

PAI ranges from 0 to 1:

- PAI ≥ 0.45: strong justification for proactive intervention investment.
- PAI < 0.20: cost drivers largely non-addressable via care management.

E. Component 4: Intervention Timing Optimization

Given candidate set I_t and capacity limit K_{max}, intervention allocation is formulated as a constrained optimization problem:

$$\max_{\alpha} \sum_{i \in I_t} \alpha_i \cdot R_i(t) \cdot P(\delta_{ik} = 1)$$

subject to: $\sum_i \alpha_i \leq K_{max}$, $\alpha_i \in \{0,1\}$

where α_i is the binary intervention decision, $R_i(t)$ is the expected cost reduction from intervention, and $P(\delta_{ik} = 1)$ is the estimated inflection probability. This formulation prioritizes members with the highest expected return adjusted for inflection likelihood. The

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problem is solved exactly as a 0–1 knapsack for smaller capacities ($K\_max \le 500$) and approximated via greedy heuristics for larger scales.

F. EGCIF Metric Suite

Trajectory Prediction Accuracy (TPA): The proportion of high-cost events (above the 85th percentile within a 90-day window) that were preceded by a detected inflection signal:

TPA = |{events with prior inflection signal within CILT window}| / |{total high-cost events}|

Cost Inflection Lead Time (CILT): The average time interval (in days) between inflection detection and the first high-cost event for correctly identified members.

- CILT > 60: supports effective outreach.
- CILT > 90: enables structured care planning.

Intervention Return on Engagement (IRE): The ratio of avoided cost to intervention cost for engaged members:

$IRE = \Sigma_{i:\alpha_i=1} (C_i^{expected} - C_i^{observed}) / \text{Intervention Cost}$

An IRE > 2.0 indicates a minimum 2:1 return on intervention investment.

IV. Empirical Evaluation

A. Synthetic Cohort Dataset

Evaluation was conducted on 14 synthetic employer group cohorts constructed to reflect the structural characteristics of self-insured employer group populations across size tiers: four large groups (5,000–18,000 members), six mid-market groups (1,000–4,999 members), and four small groups (250–999 members). Cohort construction followed established synthetic healthcare data generation procedures calibrated to MEPS (Medical Expenditure Panel Survey) utilization distributions and employer group claims benchmarks published by the Health Care Cost Institute [17]. Total dataset: 187,400 member-years across 36-month observation periods. Cost concentration in the synthetic cohorts matched documented population norms: top 1% of members averaged 23.4% of total costs; top 5% averaged 52.1%.

B. Trajectory Segmentation Stability

Trajectory class assignment stability was evaluated by measuring the quarter-over-quarter class retention rate for members not experiencing a genuine clinical status change. Across all 14 cohorts, mean class retention rate was 87.3% (range: 82.1% -- 91.8%), compared to 71.4% stability for annual point-in-time risk score quintile assignments in the same populations. The higher stability of trajectory class assignments reflects the longitudinal smoothing effect of 12-month rolling windows, which absorbs transient utilization variation that produces volatile annual score shifts.

C. Inflection Detection Performance

EGCIF inflection detection was evaluated against three baseline approaches: (1) annual risk score threshold (members crossing the 80th percentile risk score), (2) high-cost claimant identification (members with trailing 3-month expenditure exceeding the 90th percentile), and (3) disease management flag triggers (members with new chronic condition diagnosis codes in claims). Results are presented in Table I.

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Detection Method	TPA (%)	CILT (days)	False Pos. (%)	PAI Coverage
EGCIF (CUSUM + Transition)	76.4	94.2	9.8	0.68
Annual risk score threshold	58.1	41.3	22.4	0.41
High-cost claimant ID	41.7	0.0	6.2	0.29
DM flag triggers	52.3	67.8	18.1	0.37

EGCIF achieves a TPA of 76.4% with CILT of 94.2 days a 34.7% improvement in detection rate and 128% improvement in actionable lead time versus annual risk score threshold detection. High-cost claimant identification, the most common current practice, achieves 0.0 CILT by definition: it identifies members only after cost events have occurred.

D. Intervention Return on Engagement

Intervention timing optimization was evaluated by comparing IRE under EGCIF-optimized assignment versus three baseline assignment strategies: random selection from the inflection candidate pool, highest-risk-score prioritization, and highest-projected-cost prioritization. EGCIF optimization achieved IRE = 2.41 (USD 2.41 avoided cost per USD 1.00 intervention cost), compared to 1.38 (random), 1.62 (risk score), and 1.89 (projected cost). The IRE advantage of EGCIF optimization reflects the joint optimization over inflection probability and marginal cost reduction return: members with moderate inflection probability but high intervention response rates are correctly prioritized over members with high inflection probability but low clinical modifiability.

V. Enterprise Implementation Architecture

EGCIF is designed for integration with enterprise benefits administration infrastructure. Three data source types are required: monthly pharmacy claims and medical claims feeds (available through benefits administrator data pipelines), member eligibility and demographic files (available through HR information systems), and chronic condition registry data (constructed from ICD-10 code sequences in claims history). Analytics computation is structured as a quarterly batch process with monthly inflection signal updates, compatible with enterprise data warehouse and BI platform environments.

Employer group care management workflow integration is achieved through a priority queue output that delivers ranked intervention candidate lists, CILT estimates, and recommended outreach protocols to care management platforms (Healtheon, Accolade, or equivalent). The PAI is computed and reported to employer group leadership on a semi-annual basis as a strategic indicator of proactive intervention program opportunity.

Data governance requirements: EGCIF operates on de-identified claims data in compliance with HIPAA Safe Harbor provisions. Employer group population size must exceed 250 members to ensure re-identification risk remains below HIPAA-acceptable thresholds for individual-level trajectory modeling. Groups below this threshold are evaluated at the aggregate trajectory distribution level without individual-member inflection detection.

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VI. Discussion

The observed mean Cost Inflection Lead Time (CILT) of 94.2 days reflects a material shift in the temporal dynamics of employer-sponsored healthcare cost management. This magnitude of lead time is not merely statistically significant it is operationally decisive. A three-month forward signal enables the full deployment of longitudinal care interventions, including early care coordination, pre-emptive scheduling of preventive services, closure of chronic care gaps, and structured enrollment into disease management pathways. In contrast to retrospective identification frameworks, which operate at or near the point of cost realization, this expanded intervention window supports upstream clinical engagement. The net effect is a transition from ex post cost containment to ex ante cost avoidance, fundamentally altering the intervention frontier.

From a systems perspective, the Population Addressability Index (PAI) results further contextualize where proactive strategies are economically viable. Across the 14 evaluated cohorts, PAI ranged from 0.31 to 0.71 with a mean of 0.52, indicating that on average over half of projected cost growth resides within a clinically actionable sub-population. Employer groups with PAI ≥ 0.55 exhibit sufficient concentration of modifiable cost drivers to justify sustained investment in dedicated care management infrastructure, including nurse-led outreach, digital engagement platforms, and condition-specific intervention programs. Conversely, cohorts with PAI ≤ 0.30 are dominated by stochastic or low-modifiability cost drivers catastrophic events, major trauma, or neonatal intensive care utilization, where traditional care management yields diminishing marginal returns. In such contexts, optimization strategies should pivot toward financial risk mitigation mechanisms including stop-loss structuring, reinsurance layering, and carrier contract renegotiation, rather than clinical intervention scaling.

Notwithstanding these findings, the evaluation is constrained by its reliance on synthetic cohort data. While trajectory segmentation and inflection detection components are parameterized using population-level claims benchmarks, real-world employer populations frequently deviate from these statistical priors. Industry-specific occupational risks, regional practice pattern variation, provider network effects, and workforce demographic skews can materially influence both baseline trajectory distributions and transition dynamics. Optimal implementation of EGCIF therefore necessitates a calibration layer, wherein trajectory class boundaries, residual variance parameters, and detection thresholds are re-estimated using employer-specific historical claims data. This ensures alignment between model assumptions and the empirical risk structure of the target population, preserving both sensitivity in inflection detection and precision in intervention targeting.

VII. Conclusion

This paper presented a longitudinal predictive analytics architecture, the Employer Group Cohort Intelligence Framework (EGCIF), a proactive healthcare cost governance architecture of longitudinal predictive analytics in self-insured employer group settings. EGCIF directly overcomes the structural constraint of traditional employer health analytics that is the time lag between the emergence of the cost and the observability of the cost by the analytics system. The framework operationalizes the cohort intelligence to anticipate accelerations of cost trajectories ahead of its becoming manifest as claims expenditure to replace the retrospective claims-based identification with forward-looking decision support.

The empirical validation shows that EGCIF can achieve a trajectory prediction accuracy of 76.4% of high-cost events with a mean Cost Inflection Lead Time of 94.2 days which is a clinically actionable intervention window. The 2.41x Intervention Return on Engagement validates that efforts by management to accomplish trajectory-targeted outreach and care management accomplishments result in more than twice the cost of the management efforts in avoiding expenditure. The Population Addressability Index helps benefit leaders to better allocate resources across employer groups with 250 to 18,000 members, respectively.

EGCIF, in combination, provides a rigorous and scalable methodology of transforming the employer-sponsored healthcare cost management paradigm, despite not being retrospective reporting, to an active intervention paradigm. It provides enterprise benefits and analytics leaders with a decision-grade framework that integrates actuarial analysis, clinical intervention logic, and operational capacity constraints - enabling them to engage in high-risk member population more productively and cost-effectively.

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