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Evaluating the Impact of Prospective vs. Retrospective Analytics on Risk Score Accuracy and Revenue Integrity

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***Abstract*—Risk adjustment plays a crucial role in making sure payments in value-based care programs like Medicare Advantage and the ACA marketplaces fairly reflect how sick patients really are. Health plans depend on accurately capturing each patient's conditions to calculate risk scores and match reimbursement to clinical complexity. Until now, most organizations have leaned heavily on retrospective analytics—looking back at charts and claims after visits—to find missed HCC codes and fix documentation gaps. With better data integration and advances in AI, prospective analytics at the point of care are emerging as a powerful complement, helping clinicians identify and document conditions in real time. In this paper, we compare prospective and retrospective approaches across three key dimensions: how accurately they capture risk scores, how well they support revenue integrity, and what operational burden they create. Using a hypothetical Medicare Advantage population and realistic program assumptions, we contrast how each method uses clinical signals, documentation workflows, and coding steps over the course of a year, and we estimate outcomes such as RAF score improvement, closure of coding gaps, audit exposure, and return on investment. Our analysis suggests that prospective analytics improve the timeliness and completeness of risk capture, while retrospective programs are still needed to clean up remaining gaps and errors.**

Keywords—Risk adjustment, Medicare Advantage, prospective analytics, retrospective analytics, RAF score, HCC, revenue integrity, value-based care, AI in healthcare.

I. INTRODUCTION

Risk adjustment is the way government and commercial health plans make sure payments match how complex their members' health needs really are. In models like the CMS–HCC framework, each member gets a risk score based on who they are (age, gender, etc.) and which conditions are properly documented during a set time period. Those scores drive plan payments, quality bonuses, and ultimately whether value-based contracts are financially sustainable.

Getting risk adjustment "right" rests on three basics:

1. Capturing all the important diagnoses during the year, not just a few.
2. Prospective versus retrospective
3. Documenting those conditions in a way that meets coding and regulatory rules (for example, clearly showing that the condition was Monitored, Evaluated, Assessed, or Treated—MEAT).
4. Sending in accurate diagnosis codes on time so they truly reflect the member's current health.

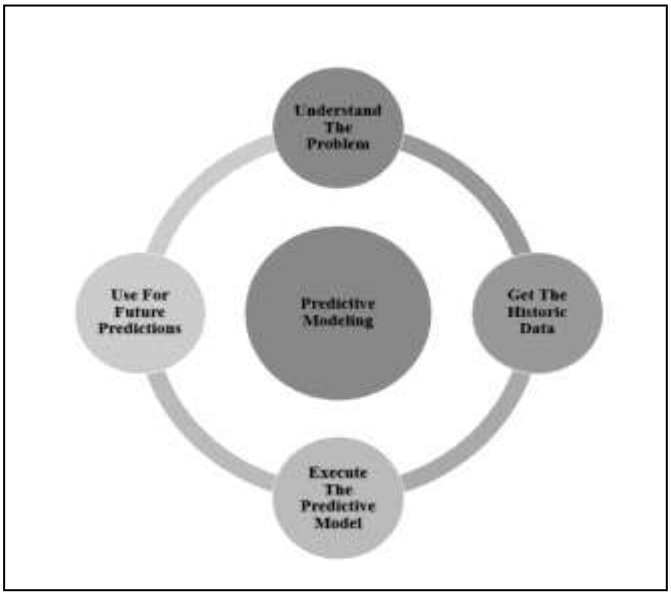

Fig. 1. Predictive analytics process

For years, most organizations have relied on retrospective analytics looking backwards, often near the end of the year. Typical activities include reviewing charts after claims are submitted, running vendor-led coding projects, and doing targeted audits to find missed HCCs or incorrect codes. These retrospective programs can bring in substantial missed revenue and improve coding quality. At the same time, they are labour-intensive, heavily concentrated at year-end, and do very little to change what happens during the actual visit.

New technology is changing that picture. Better EHR integration, stronger interoperability, and AI tools that can summarize charts in seconds now make prospective analytics possible. Instead of looking back months later, organizations can flag suspected conditions and documentation gaps before or during the appointment. By surfacing clinical clues—like medications, lab trends, imaging results, and prior-year diagnoses—prospective tools help clinicians confirm active conditions and document them correctly in real time. This supports better care and more accurate risk scores.

Even with this shift, payers and providers still face a practical question: How much extra value does prospective analytics add beyond existing retrospective programs, and what is the right mix of the two to get accurate risk scores and protect revenue?

This paper takes a structured look at that question. We compare prospective and retrospective analytics and examine their impact on:

- **Risk score accuracy:** how complete and correct RAF scores are at both the member and population levels;

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- **Revenue integrity:** how well payments match true disease burden, how resilient they are under audit, and how much clawback risk is reduced;
- **Operational efficiency:** how work is distributed across the year, how much burden falls on providers, and what the programs cost to run.

Our main contributions are threefold:

1. We offer a clear framework that distinguishes prospective and retrospective analytics across data sources, workflows, and intervention points throughout the member year.
2. We introduce a conceptual evaluation model using a hypothetical Medicare Advantage population to compare how each approach affects RAF scores, revenue, and audit risk.
3. We provide practical implementation guidelines and metrics to help organizations design a balanced, closed-loop risk adjustment program that combines the strengths of both prospective and retrospective analytics.

II. Background and Related Works

A. Risk Adjustment and RAF Scores

Risk adjustment is designed to pay health plans fairly when they care for sicker, more complex populations. In the CMS–HCC model, each diagnosis that maps to an HCC adds a certain "weight" to a member's risk score. When these diagnosis weights are combined with demographic factors, they produce the member's Risk Adjustment Factor (RAF). The overall RAF across the plan's membership then plays a major role in determining total reimbursement for the contract year.

When important chronic conditions are under-documented or under-coded, RAF scores are lower than they should be. This can lead to revenue shortfalls and leave plans with fewer resources to support high-risk members. The opposite problem—over-documentation, unsupported diagnoses, or coding that does not follow guidelines—can inflate RAF scores, creating audit exposure and the risk of repayments. Getting RAF right is therefore both a financial and a clinical imperative.

B. Retrospective Analytics

Retrospective risk adjustment looks backward, focusing on claims and documentation after encounters have already occurred. Common activities include:

1) Retrieving charts and having coders review them near year-end.

2) Running "look-back" analyses on historical encounters to find missed HCCs.

3) Working with vendors to re-code charts and submit additional diagnoses when the documentation supports them.

4) Performing post-submission audits to correct incorrect or unsupported codes.

These retrospective reviews are widely used in Medicare Advantage and ACA plans because they can recover missed risk and uncover long-standing documentation issues. At the same time, they have clear limitations:

1) Timing: Reviews may occur months after the visit, when the clinician's memory is limited and care decisions are already in the past.

2) Labor intensity: Large teams may be needed to retrieve, organize, and review charts.

3) Limited impact on care: Coding improvements do not change what happened during the visit itself.

4) Audit exposure: If retrospective coding becomes too aggressive and is not tightly governed, it can raise compliance concerns and attract audits.

C. Prospective Analytics

Prospective risk adjustment takes a forward-looking view. It uses longitudinal information—past diagnoses, medications, lab and imaging results, and even social determinants—to build a "suspect list" or risk profile for each member before a visit. During pre-visit planning or at the point of care, clinicians see suspected conditions and prompts that help them decide what needs to be assessed, treated, and documented.

Key elements of prospective analytics include:

1) Pre-visit chart review to flag suspected chronic conditions or gaps in annual recapture;

2) Point-of-care prompts in the EHR that remind clinicians to address and document those conditions;

3) Real-time capture of diagnoses with supporting MEAT elements;

4) Proactive outreach to bring high-risk members in for visits when they have not been seen recently.

When done well, prospective programs can make documentation more complete, support earlier interventions, and ease the end-of-year crunch. However, they are not plug-and-play. They require strong data integration, thoughtful workflow design, and active provider engagement to avoid alert fatigue and added burden for clinicians.

D. Revenue Integrity and Audit Environment

Regulators are paying closer attention to risk adjustment, with a growing focus on documentation integrity and recovery of overpayments. Retrospective programs that emphasize recapturing revenue without clear clinical engagement can be seen as purely financial and may draw audit scrutiny.

Prospective programs, in contrast, are built around real-time clinical validation. Diagnoses are confirmed and documented in the context of active care, which strengthens the connection between risk scores and the services actually delivered. This alignment can support revenue integrity and potentially reduce audit risk, as codes are more clearly tied to current clinical evidence and ongoing management.

III. Methodology

To compare the impact of prospective and retrospective analytics, we use a conceptual study design that could realistically be applied by a health plan or a large provider group in a risk-bearing arrangement. The numbers we present are illustrative rather than drawn from a live dataset, but the same framework could be re-run using actual claims and clinical data.

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A. Population and Data Sources

In this model, we look at a Medicare Advantage plan with 100,000 enrolled members over a single contract year. For each member, we assume access to the following data:

1) Administrative claims (inpatient, outpatient, professional, and pharmacy);

2) EHR data, including problem lists, progress notes, lab results, imaging reports, and vital signs;

3) Prior-year diagnoses and HCCs;

4) Demographic information needed for risk adjustment.

All of these data are brought together in a centralized analytics platform that supports both retrospective and prospective workflows.

B. Study Arms

We compare three conceptual program designs that reflect different levels of maturity.

1) Baseline: Standard Retrospective Only

- Year-end chart review focused on a subset of high-cost members;
- Manual coder review of selected encounters;
- Minimal or no pre-visit support for risk adjustment.

2) Enhanced Retrospective + Basic Prospective

- All baseline activities;
- Simple suspect lists for common chronic conditions shared with clinicians ahead of Annual Wellness Visits;
- Limited EHR integration, mainly to deliver these lists.

3) Integrated Prospective–Concurrent–Retrospective Model

- Prospective analytics (supported by AI or advanced rules) that generate member-level risk profiles and suspected conditions;
- Point-of-care prompts embedded in the EHR with guidance aligned to MEAT documentation standards;
- Concurrent coder review for high-risk encounters before claims are submitted;
- A smaller, more targeted retrospective review focused on remaining gaps.

C. Metrics

We evaluate each program design across three main dimensions.

1) Risk Score Accuracy

- RAF completeness (%): the share of expected HCCs (based on full clinical data) that are actually captured and submitted;
- RAF stability: year-over-year variation in member-level RAF scores;
- Under-coding rate: the percentage of members whose true clinical burden is meaningfully higher than their recorded RAF.

2) Revenue Integrity

- Payment accuracy (%): how closely recorded RAF scores match clinically expected RAF at the population level;
- Audit finding rate: the number of diagnoses removed or downgraded during audits per 1,000 members;
- Net revenue impact: incremental revenue retained after any audit-related adjustments.

3) Operational Efficiency

- Coder hours per 1,000 members for both retrospective and concurrent review;
- Number of provider alerts per visit and acceptance rate;
- Cost per incremental RAF point, capturing technology, vendor, and staff effort.

D. Analytic Approach

We follow a four-step approach.

1) Establish a "Clinical Truth" Benchmark:

Using the full set of encounters, lab and imaging results, and longitudinal history, a panel of clinicians and coders identifies an approximate "gold standard" list of active conditions and associated HCCs for a sample group of members. This benchmark represents the maximum attainable RAF under ideal documentation.

2) Simulate Each Program Design:

- Which encounters are touched (for example, only high-cost members in the baseline model versus broader coverage in the integrated model);
- The likelihood that a missing HCC is identified and documented;
- The likelihood that a previously documented diagnosis without adequate MEAT support is corrected or removed.

3) Compute Expected Outcomes:

- RAF completeness, by comparing captured HCCs to the benchmark;
- Net revenue, based on contract payment rates and expected audit adjustments;
- Operational costs, including coder and clinician effort as well as vendor and platform costs.

4) Scenario and Sensitivity Analysis:

Finally, we test how sensitive the results are to changes in key assumptions. We vary factors such as a more aggressive audit environment, differences in vendor performance, and levels of provider engagement. This helps assess how robust the conclusions are under different real-world conditions.

IV. Results and Discussions

The results are measured using following metrics based on the equations of methodology.

A. Why Prospective Analytics Improve Risk Score Accuracy

Prospective analytics pull together a member's history and real-time signals so that chronic conditions and key

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diagnoses can be addressed during the visit, not months later. This approach:

1) Improves timeliness

- Documentation happens close to the clinical decision.
- Reduces reliance on memory and post-hoc chart review.

2) Improves completeness

- Uses labs, imaging, medications, and prior diagnoses at the point of care.
- Helps recapture chronic conditions that might be missed in routine visits.

3) Strengthens clinical validity

- Diagnoses better reflect the member's current health status.
- Records are easier to defend during audits.

B. The Continuing Role of Retrospective Programs

Prospective analytics add important capabilities but do not eliminate the need for retrospective programs. Retrospective review remains important because:

- Not every member has encounters suitable for prospective review.
- Some documentation issues only appear when claims and charts are analyzed over time.
- Payer rules and coding guidelines can change mid-year and must be reconciled after the fact.

Retrospective analytics are especially useful for:

- Identifying recurring documentation gaps across providers or specialties.
- Highlighting training needs for clinicians and coders.
- Addressing residual under-coding in members with complex histories.
- Validating coding patterns and correcting errors before or during audits.

The goal is to "right-size" retrospective work, so it focuses on remaining, less predictable gaps once prospective and concurrent methods manage the routine ones.

C. Balancing Provider Burden and Data Quality

To avoid overwhelming clinicians, prospective programs should be designed with provider workload in mind.

Key design principles include:

- Limit the number of prompts to a small set of high-value suspects per visit.
- Explain each suggestion clearly, for example:
  - "Chronic kidney disease suspected based on eGFR trend and ACE inhibitor use."
- Make action easy, ideally via:
  - One-click acceptance,
  - Templates that automatically capture MEAT elements.
- Align prompts with workflow, placing them at natural points such as:
  - Pre-visit planning,
  - The assessment and plan section.

When designed this way, prospective tools can reduce documentation burden by organizing information and highlighting what matters most, rather than adding noise.

D. Revenue Integrity and Compliance Considerations

Prospective programs support revenue integrity and compliance by tying diagnoses directly to active care. They help:

- Ensure risk scores reflect real, actively managed conditions.
- Strengthen the link between diagnosis, treatment, and outcomes in the clinical note.
- Promote more consistent documentation across providers.
- Improve the organization's audit position because codes are supported by contemporaneous notes.

To maintain this alignment, organizations should:

- Involve compliance teams early in program design.
- Ensure suspect logic, prompts, and policies follow current coding guidelines.
- Explicitly avoid encouraging unsupported up-coding.

This helps keep improvements in risk scores both sustainable and defensible.

E. Limitations of the Conceptual Analysis

The analysis in this paper is conceptual and uses illustrative data. As such:

- Numerical examples are intended to show relative impact, not exact real-world results.
- Actual outcomes will depend on factors such as:
  - Population mix and baseline coding performance,
  - Maturity of EHR integration and data quality,
  - Provider engagement, training, and compensation models,
  - Capabilities of the analytics platform

Even with these limitations, the main conclusions are consistent with what many organizations observe:

- Prospective analytics tend to improve the accuracy and stability of risk scores.
- Retrospective programs remain necessary but can become more targeted and strategic.

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- Together, they support a more balanced approach to risk adjustment that aligns with both clinical practice and regulatory expectations

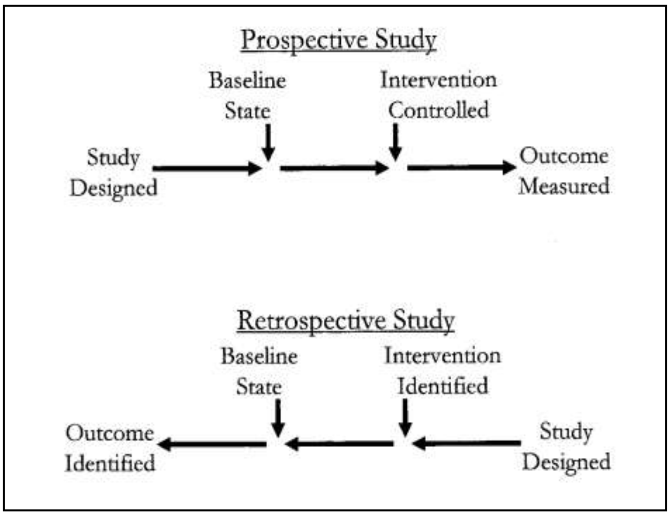

Fig. 2. Prospective versus retrospective study design. In a prospective study, the baseline state of the subjects is determined, the controlled intervention is applied, and then the outcome is measured. In a retrospective study, the intervention, baseline state, and outcome are obtained from existing information that was recorded for reasons other than the study.

V. CONCLUSION

Risk adjustment is evolving from a predominantly retrospective, year-end activity to a continuous, data-driven process embedded throughout the care journey. Prospective analytics, enabled by integrated data platforms and AI, can significantly improve the timeliness and completeness of diagnosis capture, leading to more accurate RAF scores and enhanced revenue integrity. Retrospective programs still play a critical role in closing residual gaps and validating documentation, but their emphasis shifts from broad, manual reviews to targeted, insight-driven audits.

This paper has provided a structured framework to compare prospective and retrospective analytics on risk score accuracy, revenue integrity, and operational burden. Using a hypothetical Medicare Advantage population, we illustrated how an integrated prospective–concurrent–retrospective model can improve RAF completeness, reduce audit risk, and optimize resource utilization.

Future work may include:

- Empirical evaluations using multi-year datasets from Medicare Advantage or ACA plans;
- Comparative studies across different AI vendors and EHR integration models.
- Research into fairness and equity impacts, ensuring that prospective analytics do not inadvertently widen disparities in documentation or reimbursement for vulnerable populations.

As value-based care continues to expand, organizations that invest in balanced, clinically grounded risk adjustment programs will be better positioned to sustain financial performance while delivering high-quality care. Prospective and retrospective analytics are not competing paradigms, but complementary components of a single, closed-loop risk adjustment ecosystem.

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