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Detecting and preventing premium billing variances in ASO/ASC Health Plans: A controls-first analytics framework for eligibility-to-invoice integrity

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Abstract

The research presented here introduces a Controls-First Analytics Framework to minimize premium billing variance in Administrative Services Only (ASO) and Administrative Services Contract (ASC) health insurance plans. Healthcare financial ecosystems, with their asynchronous data processing between employer Human Resource Information Systems (HRIS), Third-Party Administrators (TPAs) and carrier billing systems, often undermine the quality of the eligibility-to-invoice process (Patabendige & Hopkins, 2025). Current detective controls, with their emphasis on ex-post audits and post-payment reconciliation, are reactive and lead to financial losses, inefficient processing, and poor audit trail (Ogedengbe et al., 2022).

This research proposes a proactive model with controls integrated in the data stream. The framework comprises three main components: (1) Algorithmic Eligibility Validation (AEV) at data input, (2) automated transaction reconciliation mechanisms and (3) variance classification using a variance taxonomy. This methodology is in line with new research on financial reconciliation and continuous auditing, which show substantial gains in accuracy and efficiency (Khan & Mita, 2024).

The architecture is tested using operational data simulations, as well as failure scenarios such as retrospective terminations, tier mapping discrepancies and demographic eligibility errors. The framework is evaluated in terms of Variance Reduction Rate (VRR) and Mean Time to Resolution (MTTR). Results show significant reductions in the number of cycles required to resolve exceptions, and improved audit preparedness through automated, non-repudiable documentation (Karagoz, 2025).

The research offers a systems-based, scalable approach to enhance financial process integrity in health care billing, especially in resource restricted and high-volume administrative operating models.

Keywords: Analytics; Billing; Controls; Detecting; Framework

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1. Introduction

One of the most complicated issues of data reconciliation in the present healthcare finance is the administration of self-funded health plans that are usually organized either in Administrative Services Only (ASO) or Administrative Services Contract (ASC) arrangements. In such schemes, claims and premiums are kept by the plan sponsor, whereas operational activities like eligibility management and billing are outsourced to Third-Party Administrators (TPAs) or insurance companies (Onyenahazi, 2025). The monthly premium invoice lies at the heart of this relationship and should be correct in reflecting the eligibility information of the plan sponsor at the time of billing. Once again, however, this alignment can be easily broken by discrepancies among distributed data systems.

1.1. Economic Impact of Billing Leakage

The main problem of ASO/ASC plan administration is that billing leakage is defined as excess payment or under-benefit of the premiums because of the inaccuracy of the eligibility data. Even tiny error rates may result in huge financial losses in large-scale health plans, with thousands of eligibility transactions per month (Patabendige & Hopkins, 2025). Detective controls have long been a traditional way of organizing organizations, as they conducted periodic audits and did a post-payment reconciliation to detect discrepancies after invoices were processed (Ogedengbe et al., 2022).

Though these methods bring certain degree of control, they are fundamentally responsive and frequently limited by contractual recovery provisions and delays in the administration. Consequently, much of the financial leakage is not brought back and this affects the operational efficiency as well as the fiduciary accountability.

1.2. Data Asynchronicity and Systems Engineering Challenges

Within the systems engineering approach, the healthcare billing cycle is a distributed data ecosystem with a number of autonomous platforms, such as employer HRIS, TPA eligibility systems, and carrier billing engines. The variances are often caused by data asynchronicity, which occurs when some systems are not updated with the changes in another system within the same billing cycle (Khan and Mita, 2024).

An example of this is the so-called retroactive termination situation where the status of an employee about their eligibility is applied after the billing snapshot has already been created. This brings about a misfit that needs to be corrected in retrospect which is usually hard to follow and align effectively. Lack of system-level controls and validations compounds these issues, resulting in discrepancies in billing results.

1.3. Transitioning to a Controls-First Architecture

In an effort to deal with these systemic problems, this study suggests a Controls-First Analytics Framework, which integrates validation and reconciliation controls into the data pipeline. The framework does not consider reconciliation a post-billing process but instead proactive controls are incorporated at the point of data ingestion and processing.

This practice aligns with the latest research in automated financial systems that highlights the importance of continuous monitoring and real-time validation as key elements of data integrity (Khan & Mita, 2024; Karagoz, 2025). The framework turns the billing operations into a proactive, system-driven control environment by introducing algorithmic validation rules, transaction-level reconciliation, and standardized classification of variance, as well as turning billing operations into a reactive audit operation.

Moreover, this model can be consistent with the bigger concepts of Enterprise Risk Management (ERM) as it entails incorporating control logic into the operational processes, thus helping to make audit preparedness and limiting exposure to financial and regulatory risks. The outcome is an architecture that can be scaled and repeated and can ensure high fidelity between eligibility information and billing results.

2. Literature Review

The discussion of healthcare financial management has shifted its main orientation towards actuarial pricing to a more general orientation of operational data integrity and reliability of systems. With the further digitalization of healthcare administration, numerous data systems will come together, which brings in new risks concerning the quality of billing, financial leakage, and compliance with audit (Onyenahazi, 2025; Wager et al., 2021). The synthesis of the literature is conducted in three main areas; billing variance and financial leakage, switching to automated auditing and regulatory frameworks that determine governance in the healthcare financial systems.

2.1. Taxonomy of Variance and Financial Leakage

Billing variance in self-funded health plans is mainly motivated by inconsistencies between the eligibility information and the premiums that are billed. Such discrepancies frequently lie in disconnected data ecosystems, in which the various systems handle enrollment, eligibility and billing independently (Patabendige & Hopkins, 2025).

Research indicates that revenue leakage frequently arises from timing mismatches, commonly referred to as data latency, where eligibility updates are not synchronized with billing cycles (Ogedengbe et al., 2022). This is especially problematic in healthcare systems, as the number of transactions is huge, and there is a regulatory necessity to make correct financial reporting. It is estimated that organizations can incur losses of between 1-3 percent of total premiums spent on unresolved billing differences (McKinsey & Company, 2023).

To tackle them, researchers state that it is essential to create structured taxonomies of variances that divide them into actionable categories, e.g., the temporal (timing-based), structural (data mapping), and calculation-related ones (Wager et al., 2021). This categorization helps organizations to go beyond detection to root-cause analysis and overall correction.

2.2. Manual Auditing vs. Algorithmic Integrity

Conventional methods of audit in the healthcare finance have been based on manual reconciliation methods, which tend to be periodical, sample based and consume resources. Although such ways offer certain monitoring, they are per se narrow in scope and scalability (O'Leary, 2017).

The latest developments in the financial technology allowed the use of automated reconciliation systems that can examine full datasets on a real-time basis. Such systems greatly enhance the levels of detection and save time to detect and address discrepancies (Khan & Mita, 2024). Algorithms and machine learning techniques that make continuous auditing possible enable organizations to switch to anomaly detection, instead of reactively fixing errors (Appelbaum et al., 2017).

In addition, automated systems decrease chances of human error and sampling bias, where all the transactions are considered and not just a few. Such a transition is in line with systems engineering concepts and the continuous improvement of data quality and operational performance is provided by feedback loops.

2.3. Regulatory Drivers and Governance Standards

In the area of healthcare finance, there is a strict regulatory framework, requiring the quality of data, as well as accountability. Health Insurance Portability and Accountability Act (HIPAA) puts in place the integrity and security of health information, and the Affordable Care Act (ACA) focuses on the transparency and responsibility in healthcare expenses (Rouse, 2020).

Besides regulations in healthcare, more general governance frameworks like the Committee of Sponsoring Organizations of the Treadway Commission (COSO) Enterprise Risk Management (ERM) framework offer organized ways of incorporating internal controls into the organizational processes (COSO, 2017). Likewise, the national institute of standards and technology (NIST) Cybersecurity Framework has been gradually implemented on financial data systems to provide integrity, traceability, and resiliency (NIST, 2024).

All these frameworks support the necessity to have embedded controls in data pipelines to enable a transition towards the continuous monitoring and audit-ready systems. Copyrighting operational processes with these standards would help organizations increase their compliance and minimize the financial and regulatory risks.

2.4. Synthesis: Toward an Integrated Controls Framework

In the literature, there is a definite agreement: due to the complexity of the contemporary healthcare billing systems, there is a need to shift away to manual, retrospective systems to integrated, automated control systems. The existence of disjointed data environments and issues with constant synchronization are not one-time wastes, but the property of the modern healthcare system (Wager et al., 2021).

A good solution should thus be able to have real-time validation, standardized variance classification and monitoring mechanisms. Integrating the concepts of financial auditing, data engineering, and enterprise risk management, organizations can have a more robust and precise billing infrastructure. The present synthesis is the basis of the Controls-First Analytics Framework that will be presented in this study.

3. Methodology: The Controls-First Framework

This paper takes a systems engineering/data integrity approach to redesign the eligibility-to-invoice pipeline of ASO/ASC health plans. The Controls-First Analytics Framework conceptualizes the billing process as being a closed-loop system where internal controls are directly embedded within the data architecture instead of the controls being implemented as an external audit process (Khan and Mita, 2024; Appelbaum et al., 2017).

The methodology is structured into four sequential stages: (1) systems mapping and data ingestion, (2) algorithmic validation, (3) automated reconciliation, and (4) exception classification and resolution. Such a stratified method allows tracking and real-time identification of the billing variances.

The mapping of systems and data ingestion is included in 4.1 Systems Mapping and Data Ingestion.

The initial step is to map the data ecosystem, in order to look at all the sources of the billing process. Various systems are the sources of data in a typical ASO/ASC environment: the Human Resource Information System (HRIS) of the employer, the TPA eligibility platform, and the carrier billing engine (Wager et al., 2021).

To ensure consistency across these heterogeneous sources, the framework applies schema validation and data normalization techniques at the point of ingestion. These operations convert the different data formats e.g. CSV, EDI 834 and XML to a single relational format that can be analyzed downstream (O'Leary, 2017).

Normalization of data is needed to allow proper, transaction level comparisons and to remove discrepancies due to formatting variations. By enforcing data quality at entry, the framework reduces the propagation of errors throughout the billing cycle.

3.1. Algorithmic Eligibility Validation (AEV)

After normalizing data, they are fed to the Algorithmic Eligibility Validation (AEV) layer. It is a layer of rule-based validation mechanisms that are used to achieve and maintain logical consistency and early stage detection of anomalies in the pipeline.

Validation rules to be considered are:

- Logical consistency checks: Making sure that dates of coverage are not prior to employment dates and that the termination dates are in policy limits.
- Tier validation: This is done to ensure that the dependents match the assigned billing tier number.
- Eligibility criteria by age: Automatically highlighting the dependents who are above eligibility age (e.g., 26 years old according to ACA standards).

These validation mechanisms are based on a fail-fast principle, such that invalid records are flagged right away, and not passed on to go through the system. Such strategy corresponds to the best practices in automated auditors and data validation system (Appelbaum et al., 2017).

3.2. Automated Reconciliation Routines

The core analytical component of the framework is the automated reconciliation engine, which performs transaction-level comparisons between validated eligibility data and carrier invoice records.

The reconciliation algorithm is deterministic matching algorithm that is applied to match the records in the datasets based on unique identifiers (e.g., member ID and coverage period). Variances are calculated with the help of materiality based model:

$$VRr=Ir-(Er\times R)$$

Where:
VRr = variance for record *r*
IrI_rIr = invoiced premium
ErE_rEr = eligibility status (binary indicator)
RRR = contractual premium rate

Any non-zero variance is marked as an exception and has to be classified and resolved.

This is in line with automated financial reconciliation models that focus on full population testing and real time variance detection (Khan & Mita, 2024). Removing the sampling restrictions, the framework guarantees the full coverage and better detection rates.

3.3. Exception Classification and Variance Taxonomy

The framework includes a hierarchical classification scheme to group the detected variances into various failure modes: in order to handle large amounts of detected variances.

- Temporal variances (timing-related): Coming as a result of a lag between updates of eligibility and billing cycles (e.g., retroactive terminations).
- Data mapping errors (structural variances): The consequence of differences in the plan codes, benefit structures or system mappings.
- Calculation variances (rate differences): Due to wrong pricing or faulty pricing reasoning.

This taxonomy makes each exception specific by addressing each to the right functional area hence saving on the resolution time and enhancing the level of operational efficiency. Methods of classification have been demonstrated to improve the workflow of audit and decrease processing delays of high-volume financial systems (O'Leary, 2017).

3.4. Continuous Monitoring and Audit Documentation

The last phase of the methodology is continuously monitoring and being audit ready. Each step of the reconciliation process is recorded within a centralized, tamper resistant system which keeps a full audit trail of the data inputs, variances identified and resolution measures taken.

The system will produce an evidence package that is audit ready with the following items at the end of each billing cycle:

- Source data files (billing and eligibility)
- Variance reports
- Exception resolution logs
- User activity records

This automated documentation mechanism complies with the current standards of auditing which give priority to transparency, traceability, and reproducibility (Karagoz, 2025; COSO, 2017).

3.5. Verification and Validation (V&V)

A verification and validation (V&V) protocol is used to test the effectiveness of the framework by the use of simulated, de-identified datasets. The result of the system is checked with a reference set of data (gold standard) based on manually audited records.

The performance is evaluated based on:

- Precision: the percentage of the correct variances identified.
- Recall: Share of overall actual variances found.

This assessment strategy will make sure that the framework can deliver high detection rates and low false positives, in line with the traditional data validation and audit analytics practices (Appelbaum et al., 2017).

4. Data Analysis and Taxonomy

The usefulness of Controls-First Analytics Framework strongly relates to the accuracy and applicability of its variance taxonomy. Raw anomaly detection cannot be used in high-volume healthcare billing settings; identified variances need to be systematized so that they can be analyzed to determine the root causes and remedial action (Appelbaum et al., 2017; Khan and Mita, 2024).

In this section, an analysis of variance patterns will be discussed based on the simulation testing results, and the dynamics of the classification, materiality and resolution of billing discrepancies.

4.1. Categorical Breakdown of Failure Modes

The analysis has shown that billing variances do not occur in a random manner but rather tend to observe some failure modes. These types are in line with the taxonomy that was established in the methodology and include systemic vulnerabilities in the data pipeline.

Temporal latency (retroactive effects): It is the most common type which makes most of the variances that are detected. It is caused when the updates of the eligibility are made on the post-generation of the billing cycle snapshot, leading to overbilling or delayed adjustments (Patabendige and Hopkins, 2025).

This dependence can be put in the form of a time differential:

$$\Delta T = Tupdate - Tinvoice$$

Positive values are those that show delayed updates and, as a result, create billing inaccuracies.

Structural mapping errors: These are due to discrepancies in the representation of plan codes, benefit structures or tier of coverage across systems. Section 10.14.20 without standardized crosswalk tables will result in false variances as the equivalent plans will seem incompatible (Wager et al., 2021).

Demographic logic violations: They are such instances that the rule of eligibility is breached, like the dependents are above the age limits that are stipulated by the policy (e.g. 26 years by ACA standards). These mistakes are often signs of ineffectiveness in validation processes in the upstream and the significance of rule-based controls (Rouse, 2020).

Identity fragmentation: This happens when one person appears in a number of systems using different identifiers to represent him or her thus resulting in a duplication of billing or incomplete reconciliation. One of the challenges in integrated health information systems known is identity inconsistencies (Wager et al., 2021).

4.2. Materiality and Impact Analysis

All variances do not have the same financial importance. The framework uses a materiality-based approach to prioritize the remediation efforts, with high impact discrepancies in mind.

In line with the Pareto principle, the analysis reveals that the percentage of variances with respect to financial impact is relatively small (McKinsey and Company, 2023). This understanding justifies the use of precision auditing whereby analytical resources are focused on high-value exceptions.

The framework proposes a measure of impact, Variance Density (Vd):

$$Vd = \frac{\text{Total Variance}}{\text{Total Premium}}$$

Higher values of Vd reflect systemic problems, e.g. structural mapping errors, and not just some anomalies. The use of this metric helps organizations to determine hot spots of certain plans, tiers and even carriers and then focus on corrective action.

4.3. Exception Cycle Time and MTTR

One of the key performance indicators of the framework is the Mean Time to Resolution (MTTR) that calculates the average time that it takes to resolve known billing variances.

Before introducing the concept of structured classification, the exception resolution processes tend to be uncoordinated hence taking up long resolution cycles. Taxonomy-based routing has been shown to greatly minimize the time of resolution since the issues are channeled to work with the relevant functional teams (Khan & Mita, 2024).

For example:

- Temporal variances are billed to the billing teams to make credit changes.

- Mapping corrections are given to data or IT teams to correct structural errors.

This organized workflow minimizes any bottlenecks in the operation and the reconciliation is more a continuous improvement process, as opposed to a reactive one.

The simulation shows that there is a considerable decrease in the number of MTTR with the introduction of automated classification and routing systems. These results are in line with the previous studies that have shown the efficiency improvement related to automated auditing and reconciliation system (Appelbaum et al., 2017).

5. Discussion and Artifacts

The Controls-First Analytics Framework is not just a design of an algorithm but also operational artifacts that provide governance, monitoring, and decision-making. Analytical products should be converted into tools that can be used in complex healthcare billing settings to ensure continued supervision and audit preparedness (COSO, 2017; Appelbaum et al., 2017).

This segment explores three fundamental artifacts that were created as part of the framework: the variance dashboard, the control-to-risk matrix and the audit-ready evidence package. These elements combined implement the framework and fill the gap between the technical analytics and enterprise risk management.

5.1. The Variance Dashboard (Operational Command Center)

The variance dashboard is the main tool of monitoring billing integrity. Instead of being a frozen reporting device, it offers real-time actionable information that allows taking proactive actions.

The dashboard has three analytical views:

5.1.1. Materiality heatmap:

This visualization combines finance variance among plans, tiers, and carriers, and shows high-risk areas according to the density thresholds of variance. Monitoring with heatmaps has become a popular type of financial analytics to assist in quick detection of systemic problems (McKinsey & Company, 2023).

5.1.2. Trend analysis panel:

This component monitors the Variance Reduction Rate (VRR) with the course of time, and the organizations can evaluate the effectiveness of controls implemented. The decreasing pattern of the structural variances is a sign of data correspondence and integration of systems.

5.1.3. Exception aging queue:

This perspective follows through on unresolved variances with regard to the timelines of resolving them which gives insight on the bottlenecks in operations. Exception aging of tracking is important in controlling the MTTR and the timely remediation (Khan and Mita, 2024).

The dashboard is the method used to centralize raw outputs of an analytical result in a centralized decision-support system.

5.2. The Control-to-Risk Matrix

The framework includes a Control-to-Risk Matrix to align the technical controls and organizational risk objectives. This artifact relates the risk categories that are identified to the analytical control and system outputs in a structured manner, which will give a systematic connection between the operation processes and the enterprise risk management (COSO, 2017).

The matrix has a number of vital purposes:

- Risk translation: Converts abstract financial risks (e.g., billing leakage, data inaccuracy) into measurable system controls
- Audit traceability: Shows the way any control will reduce a particular risk as justification of audit documentation.

- Governance correspondence: Makes sure that ERM frameworks are in line with technical implementations.

For example:

- Transaction-level reconciliation helps to mitigate capital leakage risk.
- Algorithms used to validate data are used to deal with the risk of data integrity.
- Compliance risk is addressed using eligibility logic (e.g., based on age)

Such structured mapping can assist in boosting transparency and allow auditors and other stakeholders to assess the effectiveness of internal controls.

5.3. Audit-Ready Evidence Package

One of the major innovations of the Controls-First framework is the creation of an audit ready evidence package at the end of every billing period, which occurs automatically. Conventional audit preparation methods tend to be based on manual documentation access, which is time-consuming and likely to have discrepancies (Karagoz, 2025).

Conversely, the suggested framework constantly records and collects audit-relevant data over billing lifecycle. The evidence package resulting in is:

- Source data inputs (eligibility and billing files)
- System-generated variance reports
- Detailed logs of exception resolving.
- User activity records, control execution records.

This practice will make all the audit evidence complete, consistent and easily accessible. It similarly conforms to the contemporary audit principles that focus on the transparency, reproducibility, and real-time assurance (Appelbaum et al., 2017).

Automation of the generation of evidence can help organizations save a lot of time in preparing an audit as well as enhancing the quality of financial reporting (Agyei et al., 2026).

5.4. Discussion: Scalability and Organizational Impact

Even though the Controls-First framework shows good technical performance, its effective implementation presupposes alignment of an organization and transition to data-centric governance. The billing processes should be identified as the administrative functions rather than being considered as the important aspects of the financial control systems.

Continuous audit preparedness is created by providing real-time validation, continuous monitoring, and automated documentation. This feature comes in especially handy in the context of scale and volume of healthcare services, where regulatory oversight and financial sophistication are elevated (Rouse, 2020).

Furthermore, the framework is inherently scalable. Its modular design enables organizations to scale modules - such as validation rules or classification models - to changing regulatory requirements and changes in the system (Homwe et al., 2025). This adaptability encourages the sustainability and resilience of dynamic healthcare eco systems over time.

6. Conclusion and Future Outlook

This study introduced a Controls-First Analytics Framework as a systemic approach to reducing premium billing variances in ASO and ASC health plans. The framework resolves the underlying cause of financial leakage by redefining the billing process as a data pipeline, as opposed to a retrospective accounting service, which started with data asynchronicity and poor system architectures.

The results show that the integration of validation checks, automatic reconciliation tools and the systematic classification of variances within the billing process can positively affect the data quality and efficiency of operations. Specifically, combined transaction-level validation and taxonomy-based exception management helps decrease the resolution time and increase audit traceability. The results can be compared to the previous studies that highlight the importance of continuous auditing and automated financial control systems (Appelbaum et al., 2017; Khan and Mita, 2024).

The framework helps to promote wider organizational goals in the area of governance and compliance in addition to operational benefits. The model enhances financial accountability and minimizes regulatory risk exposure by aligning with the principles of Enterprise Risk Management and providing the ability to have audits ready continuously (COSO, 2017; Rouse, 2020).

Practically, the framework provides a scaled solution that can fit various healthcare settings, specifically those with a large number of transactions and minimal administrative capabilities. Its modular structure enables incremental implementation and customization to organizational requirements and maturity of the system.

The study ought to focus on incorporating more sophisticated methods of analysis, such as machine learning and natural language processing to improve anomaly determination and automatic processing of more complicated plan documents in the future. Also, it would be possible to empirically validate the proposed model with real world datasets to enhance the generalizability of the proposed model.

In the context of the further development of healthcare financial systems towards an ever more complex system, the importance of well-developed, data-oriented control mechanisms will grow. The Controls-First methodology offers a base towards attaining sustainable billing accuracy, operational robustness, and audit-ready performance in the current healthcare eco system.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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