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DATA-DRIVEN REVENUE RECOVERY: SQL-BASED VALIDATION FRAMEWORKS FOR BILLING ACCURACY

Vaishnavi Khati
Business Analyst, Independent Researcher, London, United Kingdom

ABSTRACT
Billing accuracy is often treated as a back-office housekeeping matter rather than a source of retrievable revenue. This paper argues that treating it as the latter, and building the analytical capability to do so, is one of the more reliable ways for finance and billing operations teams to improve margin without touching pricing or headcount. Drawing on published industry benchmarks and a structured practitioner methodology, it sets out a SQL-first approach to full-population billing validation, moving beyond the sampling-based reconciliation that most operators still rely on. The paper introduces the RECOVER framework, a seven-stage methodology covering reconciliation, discrepancy extraction, segmentation, root-cause analysis, stakeholder validation, control embedding and reporting, designed to convert one-off recovery exercises into a repeatable capability. It closes with an honest account of where the approach struggles, including data quality prerequisites, the limits of correlation-based detection, and the organisational politics of reallocating analyst time to a function that rarely has a budget of its own. The intended reader is a business analyst, finance manager or billing operations lead who suspects their organisation is leaving money on the table but lacks a structured way to prove or fix it.

Keywords:
Billing validation, revenue recovery, SQL data analysis, reconciliation, gap analysis, user acceptance testing (UAT)

INTRODUCTION
Across telecoms, SaaS and other high-volume billing environments, industry research consistently reports that somewhere between 1 and 10 percent of billable revenue is never collected, not because customers refuse to pay but because it is never correctly billed in the first place (OneBill Software, 2026; Zenskar, 2026; NetSuite, 2026a; Wipro, 2026). The causes are mundane rather than dramatic: a discount that outlives its promotion, a usage event that never reaches the rating engine, a tax rule not refreshed after a regulatory change, or a manual reconciliation step nobody quite has time to do properly. Individually these look like rounding errors; at the scale of a million transactions a month, they are not.

The conventional response, periodic manual audits and sample-based reconciliation, catches only a fraction of this leakage and typically surfaces it months after the revenue has already gone. This paper sets out a different approach: full-population SQL-based validation, supplemented with Python for pattern investigation, applied continuously rather than periodically, and embedded into the organisation through the same discipline business analysts already use for requirements and testing work, namely gap analysis, user acceptance testing (UAT) and structured documentation. The proposed methodology, the RECOVER framework, treats revenue recovery as a repeatable analytical process rather than a one-off finance project. It is not a new piece of software or a vendor product; it is a way of sequencing existing tools and existing business-analyst discipline so that discrepancy detection, root-cause investigation and control embedding happen within the same cycle, rather than as disconnected activities owned by different teams that rarely compare notes.

Revenue leakage is not a new problem, but the conditions that make it worth addressing properly have changed. Billing estates have grown more complex as providers bundle usage-based charges, subscriptions, partner settlements and regulatory surcharges onto a single invoice, and each additional system in that chain is another point at which a customer's actual consumption can drift away from what finally gets billed. At the same time, finance and operations teams now have more analytical capability sitting on their own desks than they did even five years ago: cheap compute, mature SQL tooling, and Python scripting are standard business-analyst skills today rather than specialist data-team territory. Margins are under pressure across telecoms, SaaS and utilities alike, and the cost of finding another percentage point of revenue through validated billing is usually far lower than the cost of finding it through new sales or price increases, both of which carry customer-facing risk that billing correction largely avoids.

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Estimates of billing-related leakage vary by methodology and sector but are consistently uncomfortable reading: telecoms-focused research puts average industry leakage at around 1.9 percent of revenue, with some operators losing between 3 and 8 percent through internal process failures alone (OneBill Software, 2026), while a global survey of revenue-assurance experts reported a wider range of 0.5 to 10 percent (Wipro, 2026). A 2025 survey of UK telecoms professionals found that two-thirds of respondents knew leakage was a serious problem but did not know how to address it, and that nearly three-quarters of operators fail to send a bill to some customers at all, purely because of poor reconciliation between service-delivery and billing systems (Telemedia Magazine, 2026). What most of these studies agree on is that leakage is rarely caused by fraud; it is caused by data quality problems, manual processes, and a lack of interoperability between systems.

Three gaps recur across this commentary and align closely with what a working analyst sees on the ground. The sampling gap: many revenue-assurance functions still rely on sampling rather than full-population checks, which structurally misses discrepancies affecting a small subset of accounts or a specific product line. The root-cause gap: correcting an individual invoice is not the same as understanding why it was wrong, and symptom-level fixes let the same categories of error resurface every few months under a different account. The cross-functional gap: revenue leakage sits at the intersection of data, billing operations, commercial and finance, and no single function owns all of it, so validation findings can become technically accurate but commercially irrelevant if nobody with budget authority is accountable for fixing them.

The problem is also not a new discovery, even if the tooling to address it properly is more recent. Academic and practitioner research on telecom revenue assurance stretches back well over a decade, from early graduate research on building revenue-assurance capability inside telecom enterprises (Danchev, 2010) and on setting up a revenue-assurance function within a national operator (Borg, 2009), through to more recent practitioner literature that continues to frame revenue assurance as a permanent organisational capability rather than a finite project, spanning continuous monitoring, event-based monitoring and net-profit-based monitoring disciplines (Natarajan, 2022), consistent with the broader framing of revenue assurance as an ongoing set of policies, controls and technologies rather than a one-off audit (NetSuite, 2026b). What has changed is less the underlying problem than the toolset available: cheap columnar compute, mature Python and SQL tooling, and, increasingly, machine-learning-assisted anomaly detection are now realistic options for a single analyst or small team, not just organisations able to fund a dedicated revenue-assurance department. That shift, from a specialist function to a capability any BA-literate team can build, is the practical opening this paper tries to make use of.

This paper is written for business analysts, billing operations managers, finance controllers and revenue assurance leads who are responsible for, or simply curious about, the accuracy of billing output in a high-volume transactional environment. It assumes familiarity with SQL and basic Agile delivery concepts, but not with data science or specialist revenue-assurance software. It covers the detection, investigation, quantification and organisational embedding of billing discrepancies using SQL, Python and standard business-analysis process; it does not cover fraud detection specifically, the design of billing or rating engines themselves, or the evaluation of specific commercial revenue-assurance platforms, since the framework proposed is intentionally tool-agnostic and can be run largely on infrastructure most finance and business-analysis teams already have to hand. The remainder of the paper sets out the RECOVER framework and its methodological basis, presents the resulting value proposition, benefits and implementation considerations, and closes with an honest discussion of the approach's risks and limitations.

METHODOLOGY

This paper follows a structured-practitioner methodology rather than an empirical study design: it synthesises published industry benchmarks on billing-revenue leakage with a repeatable analytical framework, the RECOVER framework, distilled from practitioner experience designing and running SQL-based billing-validation exercises in high-volume telecom and SaaS billing environments. The RECOVER framework is not a piece of technology; it is a sequencing discipline for work that most billing-operations and business-analyst teams already know how to do individually: SQL reconciliation, Python-based pattern investigation, customer segmentation, gap analysis, UAT, documentation and training. Its contribution is insisting that these seven stages happen within the same cycle, owned by a clear, accountable analyst or small team, rather than as disconnected activities scattered across finance, IT and operations. Table 1 summarises the seven stages, their objective, primary technique and typical output.

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Table 1. The RECOVER Framework: Seven Stages

Stage	Objective	Primary technique	Typical output
R – Reconcile at scale	Match billing records against the full transaction population, not a sample	Data mapping across CRM, rating and billing systems using SQL	Full discrepancy list, transaction-level detail
E – Extract & isolate	Separate genuine anomalies from expected variance (credits, refunds, agreed adjustments)	Python pattern classification and outlier isolation	Clean discrepancy dataset ready for segmentation
C – Classify & segment	Group discrepancies by customer value, product line, region or error type	Segmentation analysis (rule-based or clustering)	Prioritized list ranked by recoverable value
O – Origin (root cause)	Establish why the discrepancy occurred, not just that it occurred	As-Is/To-Be gap analysis, process mapping	Documented root cause per discrepancy category
V – Validate with stakeholders	Confirm findings and proposed fixes before deployment	UAT coordination, stakeholder workshops	Signed-off remediation plan
E – Embed controls	Build the fix into the process so it does not recur	Rule changes, automated checks, BRD/FRD updates	Updated process documentation, new control point
R – Report & retrain	Communicate outcomes and train end users so the fix sticks	KPI dashboards, training sessions	Sustained accuracy, lower recurrence rate

Reconciliation at scale (Reconcile) starts with a full join across the systems that should, in principle, agree: the CRM or customer master, the usage or rating engine, and the billing or invoicing system. In practice this means SQL queries that match on customer and service identifiers, compare the expected charge (based on the customer's contracted rate and usage) against the actual billed amount, and flag any variance above a defined tolerance. Because the goal is full-population coverage rather than a sample, this needs to run efficiently against millions of rows; well-indexed joins and, where volumes are very large, a columnar warehouse rather than a purely transactional database keep this practical on a monthly or even daily cadence.

Discrepancy investigation with Python (Extract) separates genuine anomalies from expected variance, such as legitimate credits, agreed discounts or timing differences between systems. Simple classification logic, rule-based tagging, clustering on discrepancy size and frequency, or basic outlier detection narrows a raw list of flagged transactions down to a manageable set worth an analyst's time, and groups similar discrepancies together so the same root cause is investigated once rather than transaction by transaction. Segmentation (Classify) then groups the resulting discrepancy set by customer value, product line, region or error type, turning a flat list into a prioritised one, since a discrepancy affecting a small number of high-value accounts and one affecting thousands of low-value accounts call for different remediation speed and different stakeholders.

Root-cause and gap analysis (Origin) is standard business-analysis territory rather than a data-science technique: mapping the As-Is billing process for the affected discrepancy category, comparing it against the intended To-Be process, and identifying at which handoff the two diverge. UAT and stakeholder validation (Validate) then walks finance, business and IT stakeholders through the discrepancy, the proposed fix and the expected impact before go-live, catching unintended consequences before deployment rather than after. Finally, control embedding and documentation (Embed and Report) records the root cause, the fix and the new control point in updated Business and Functional Requirements Documentation, and trains the end users who operate the corrected process, which is what prevents the same discrepancy resurfacing in six months under a different account number.

Two of these techniques are worth grounding explicitly, since they carry most of the methodological weight of the Origin and Validate stages. Gap analysis, in the business-analysis sense used throughout this paper, is the structured comparison of a current As-Is state against an intended To-Be state to determine exactly where and why the two diverge, typically documented through process maps, current- and future-state diagrams and a written account of the difference between them (ModernAnalyst, n.d.). Applied to a billing discrepancy, this means mapping how a discount, tax rule or usage event is actually handled today, comparing that against how it was designed to be handled, and treating the divergence itself, not just the resulting invoice error, as the thing to be fixed. User acceptance testing plays an equivalent grounding role at the Validate stage: rather than a generic sign-off step, UAT properly run involves early and continuous involvement of the business stakeholders who will live with the fix, realistic test data drawn from production-like scenarios, and clear, pre-agreed success criteria against which the fix is judged before it goes live (Splunk, 2025). Skipping either discipline, treating gap analysis as an informal conversation or UAT as a rubber stamp, is a common way that an otherwise sound SQL-based detection exercise fails to convert into a durable process fix.

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RESULTS AND DISCUSSION

Framed conservatively and against the alternatives available, the case for a SQL-first, full-population approach rests on three measurable advantages. Speed of detection: full-population SQL reconciliation run monthly, or more frequently where infrastructure allows, surfaces discrepancies within one billing cycle rather than the multiple cycles typical of periodic audits; moving from a quarterly manual audit to monthly automated reconciliation can, in illustrative terms, compress average time-to-detection from roughly 90 days to under 30, though the exact figure depends on existing data infrastructure. Coverage: because the method checks every transaction rather than a sample, it catches discrepancies affecting small customer segments or specific product lines that sample-based audits structurally miss. Recoverable revenue and reduced recurrence: transactions that would otherwise never have been correctly billed are identified and, while still within a realistic collection window, recovered, and the recurrence rate for the same discrepancy category falls once root-cause fixes are embedded through the Origin and Embed stages. Table 2 summarises the directional improvement over the typical current-state approach across five dimensions.

Table 2. Directional Improvement Under the RECOVER Framework

Dimension	**Typical current-state approach**	**RECOVER-based approach**	**Directional improvement**
Detection cadence	Quarterly or annual audit	Monthly (or more frequent) full reconciliation	Faster detection, smaller uncollectable backlog
Coverage	Sample-based	Full population	Catches segment-specific, low-frequency errors
Root cause	Often undocumented	Mandatory gap-analysis stage	Lower recurrence of the same error category
Stakeholder buy-in	Ad hoc	Structured UAT before deployment	Fewer unintended consequences post-fix
Sustainability	Depends on individual memory	Documented and trained	Control survives staff turnover

The value proposition is not identical across sectors, and it is worth being specific about how it differs. In telecoms, the classic leakage points are configuration drift in discount and promotion engines, usage events that fail to reach the rating engine, and mismatches between CRM, network and billing systems that have grown organically over years of mergers and platform changes. In SaaS and other usage-based software businesses, the equivalent failure points sit further upstream, in the metering layer itself: missing or duplicated usage events, delayed event pipelines, and pricing-configuration errors that silently under- or over-charge a tier or overage band before an invoice is ever generated (m3ter, 2026). This matters for how the Reconcile and Extract stages are built in practice: a telecom implementation typically reconciles billing records against a rating engine and a CRM, while a SaaS implementation more often needs to reconcile invoiced amounts against a raw usage-event log first, since the earliest and cheapest point to catch a usage-based billing error is before it is rated at all, not after. The RECOVER sequencing is the same in both cases; the specific systems being joined at the Reconcile stage are not.

These are directional claims rather than guaranteed percentages; the scale of benefit in any specific organisation depends heavily on current data quality, system landscape and the resourcing given to the Origin, Validate and Embed stages, which are the stages most often shortened under time pressure.

Getting from a validated concept to a working practice involves a handful of practical decisions. On data prerequisites, the framework depends on being able to join customer, usage and billing data reliably; where these live in genuinely disconnected systems with no common key, the first piece of work is a data-integration exercise to establish that key, scoped and communicated honestly as a prerequisite rather than folded silently into the first quick win. On team and skills, a workable starting team is small: one analyst comfortable with SQL and basic Python, read access to CRM, rating and billing data, and a named commercial or finance sponsor who can authorise stakeholder time for UAT; larger organisations will want to formalise this into a small revenue-assurance function over time, but starting small on one product line or region first is lower-risk than a big-bang rollout.

On prioritisation, it is better to start with the highest-value, most tractable segment than to attempt full-population coverage across every product on day one; a single well-executed cycle through all seven RECOVER stages on a bounded scope builds credibility, and its artefacts, discrepancy documentation, a working reconciliation query set, a completed UAT, become templates for expanding scope afterwards. On change management, the Validate and

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Embed stages are where most implementations quietly fail, not because the SQL is wrong but because the organisational buy-in needed to change a live process is harder to secure than the technical fix itself; building UAT and sign-off in from the first cycle, rather than treating it as bureaucracy to minimise, is what makes the difference between a one-off recovery and a lasting capability. On governance and reporting, KPI dashboards tracking discrepancy volume, recovered value and recurrence rate by category give the function a way to demonstrate ongoing value rather than being seen as a one-off project.

The approach has real limits that are worth stating plainly rather than minimising. Detection is not the same as understanding causation: SQL-based reconciliation is good at showing that a discrepancy exists and describing its shape, but considerably weaker at explaining why on its own, and treating every statistical pattern as a confirmed root cause risks fixing the wrong thing, which is why the Origin stage exists as a mandatory human-investigation step rather than a query result. The framework only finds what the rules can describe, so entirely novel failure patterns can sit undetected until volume makes them visible some other way, a limitation shared with essentially every rules- or statistics-based detection approach. Data quality is a hard prerequisite, not a nice-to-have: where customer, usage and billing records cannot be reliably joined, matched or deduplicated, the entire method is compromised at the first stage. Recovery also has a shelf life, since a meaningful share of identified leakage will simply be uncollectable by the time it is found, and organisational resistance is common and rational rather than mere friction, since billing owners, sales teams and system owners implicated by a finding may reasonably see a validation exercise as an audit of their own performance. Aggressive tolerance thresholds also carry a real cost in false positives, and the Origin and Validate stages remain human-intensive and do not automatically scale at the same rate as the SQL layer.

Running full-population reconciliation across customer, usage and billing data also raises data-governance questions that are easy to underweight when the immediate goal is finding leakage. The RECOVER framework deliberately routes discrepancy investigation through existing CRM, rating and billing extracts rather than creating a new, separately governed copy of customer data, but even so, an analyst working across all three systems typically gains visibility into a wider slice of customer records than their day-to-day role would otherwise require, and that access needs to be time-boxed, logged and scoped to the discrepancy categories under investigation rather than left open-ended once a cycle is complete. Where the billing data includes special categories of personal information, healthcare or public-sector billing being the obvious examples, the Origin and Embed stages should also record whether a proposed fix touches how that data is collected or retained, not just how it is billed, since a process fix that quietly changes a data-retention pattern can create a compliance question independent of the revenue question it was meant to solve. None of this argues against running the framework; it argues for treating data access as a designed part of the RECOVER cycle, agreed with the same stakeholders who sign off the UAT, rather than an informal side effect of giving an analyst read access to three systems at once.

Building the business case for a first RECOVER cycle is easier when it is framed as a scoping exercise rather than a revenue guarantee. A reasonable case-development sequence starts from the transaction volume and average invoice value for the segment under consideration, applies the lower end of the published industry leakage range as a conservative planning assumption rather than an expected outcome, and treats the resulting figure as the ceiling the first cycle is testing for, not a number promised to finance in advance. Framed this way, even a first cycle that recovers well below that ceiling still produces two useful outputs: a validated, organisation-specific estimate of the actual leakage rate to replace the generic industry range, and a working reconciliation query set and UAT template that make the second cycle materially cheaper to run than the first. Organisations that instead commit to a headline recovery number before the first cycle has run tend to create exactly the kind of pressure that shortens the Origin and Validate stages under time constraints, which is, as discussed above, where the framework's durability actually comes from.

Given the sensitivity of specific commercial figures, the following case study is presented as an illustrative composite drawn from patterns commonly reported in industry practice, rather than a single named organisation's audited results. A mid-sized subscription-and-usage billing operator processing roughly 1 to 1.5 million transactions a month adopts full-population SQL reconciliation in place of a quarterly manual audit. In the first cycle, discrepancy detection surfaces a cluster concentrated in a small number of legacy discount configurations that had not been correctly time-bound, consistent with the pattern reported in the UK telecoms survey discussed above, where the overwhelming majority of operators struggled to switch off discounts on schedule. Root-cause (Origin-stage) analysis traces this to a gap between the discount-management workflow and the billing engine's expiry logic, a classic As-Is/To-Be mismatch rather than a coding bug. Following UAT and stakeholder sign-off, the fix is embedded as an automated expiry check, and discrepancy recurrence in that category falls sharply in the following cycles, illustrating the value of closing the Origin and Embed stages rather than simply correcting the flagged invoices. This composite is deliberately conservative and avoids specific pound or percentage figures,

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since real recovery outcomes vary too widely by organisation, data maturity and discrepancy type to generalise responsibly; readers building their own business case should treat the industry ranges cited above as the basis for a scoping estimate, then validate against their own transaction volumes and discrepancy categories in a first RECOVER cycle.

Over the next three to five years, two trends are likely to reshape this space. First, AI-assisted anomaly detection is increasingly being layered onto traditional rule-based reconciliation (SimplyAsk/HubiFi, 2026), but this should be read cautiously: pattern-detection models are good at surfacing candidates for investigation faster than manual rule-writing, but they do not remove the need for the Origin and Validate stages, they change what feeds into them, since an anomaly flagged by a model still needs human root-cause investigation and stakeholder sign-off before it becomes a process fix. Vendor commentary on telecom revenue assurance already lists concrete use cases for this layering: monitoring revenue metrics such as price, volume and transaction count in real time to surface deviations that a monthly dashboard would only show weeks later, and correlating call-detail-record loss between mediation and billing systems that would otherwise go unreported until a much larger discrepancy forced an investigation (Subex, n.d.). Applied inside RECOVER, this kind of model sits squarely at the Extract stage, narrowing the population of flagged transactions that a human analyst needs to look at, rather than replacing the Origin and Validate stages that still require a person to establish causation and secure stakeholder sign-off.

Second, continuous rather than periodic assurance is becoming the expected standard, particularly as cloud data warehousing makes near-real-time reconciliation technically straightforward rather than a specialist infrastructure project. For the framework proposed here, both trends are additive rather than disruptive: they change the tooling available at the Reconcile and Extract stages without changing the underlying need for structured root-cause analysis, cross-functional validation and documented control embedding that the Classify, Origin, Validate, Embed and Report stages provide. A reasonable expectation for the next few cycles of tooling is that the Reconcile and Extract stages keep getting faster and cheaper to run, while the Origin, Validate and Embed stages remain the stages on which a recovery programme's long-term success actually turns, since no amount of detection speed compensates for a root cause left unaddressed or a fix pushed live without stakeholder sign-off.

CONCLUSION

Billing accuracy sits in an unusual position: it is one of the few places a finance or business-analysis function can find real, recoverable revenue without touching price, product or headcount, and yet it is routinely under-resourced because it looks like a housekeeping task rather than a growth lever. The evidence from telecoms, SaaS and adjacent industries suggests the sums involved, typically somewhere between 1 and 10 percent of billed revenue depending on sector and methodology, are too large to keep treating this way. Full-population SQL-based validation, sequenced through a disciplined process of reconciliation, investigation, segmentation, root-cause analysis, stakeholder validation, control embedding and reporting, closes the sampling, root-cause and cross-functional gaps that leave most current approaches only partially effective.

It is not a silver bullet, and this paper has tried to be honest about where it struggles: data quality prerequisites, the limits of pattern-based detection, and the organisational effort required to make a fix stick rather than simply get an invoice corrected. For finance, billing-operations and business-analysis leads reading this with a specific suspicion that their own organisation is leaking revenue, the practical next step is not to commission a large programme, but to run a single, bounded RECOVER cycle against one high-value segment, and let the result of that cycle make the business case for the rest.

The underlying discipline is not new. Revenue assurance has been studied and practised in telecoms for well over a decade (Borg, 2009; Danchev, 2010), and the persistence of the same categories of leakage across that period says less about the difficulty of the SQL involved than about how consistently the organisational side, root-cause ownership, stakeholder validation and documented control embedding, gets under-resourced relative to the detection side. What is genuinely new is how cheaply the detection side can now be built, and how far beyond telecoms the same pattern of usage-metered, multi-system billing now extends, into SaaS, utilities and any other business that charges for consumption rather than a flat fee. The RECOVER framework's contribution is narrow but, hopefully, useful: it is a reminder, sequenced into seven named stages, that detecting a discrepancy and fixing the reason it happened are two different jobs, and that a paper claiming to close billing leakage which only does the first of those jobs has not yet finished the work.

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