Mitigating Institutional Amnesia: A Design Science Framework for Socio-Technical Query Governance in Healthcare

Samuel T Harrold, Yuimedi, Inc.

January 2026

Healthcare organizations face a "Triple Threat" of low analytics maturity, high workforce instability, and semantic technical barriers that together produce a crisis of "Institutional Amnesia." Recent data underscores the severity: 53% of healthcare CIOs have held their roles for less than three years, and 55% of informatics specialists intend to leave their positions. This churn systematically erases the tacit knowledge required to navigate complex clinical data schemas, trapping organizations in a cycle of low maturity where the rate of knowledge loss exceeds the rate of knowledge capture.

Viewed through Nonaka's SECI model of knowledge creation, the root cause is a "Socialization Failure": high turnover fractures the social networks required for mentorship, rendering the traditional apprenticeship model of informatics unsustainable. To address this failure, we employ a Design Science Research (DSR) approach, synthesizing evidence from healthcare informatics, knowledge management, and natural language processing (2024-2025 workforce and NL2SQL literature) to develop a socio-technical framework called Human-in-the-Loop Semantic Governance (HiL-SG).

HiL-SG shifts the locus of organizational knowledge from volatile human memory to durable semantic artifacts called "Validated Query Triples," each comprising a natural language intent, executable SQL, and rationale metadata. By embedding knowledge capture into the daily workflow of query generation, the framework converts the ephemeral act of analytics into permanent institutional assets. The accompanying Analytics Resilience Index (ARI) provides a measurement instrument that replaces static maturity checklists with dynamic resilience metrics, quantifying an organization's ability to sustain analytical capability despite staff churn.

A critical objection, the "Validator Paradox" (who validates the AI when experts leave?), is resolved by reframing validation through Lean "Standard Work": each validated query establishes the current known standard rather than eternal truth, functioning as a "knowledge ratchet" that prevents regression. By decoupling analytical capability from individual tenure, healthcare systems can ensure that analytics maturity advances even as the workforce evolves.

Contents

1 The Triple Threat: Institutional Amnesia in Healthcare Analytics

The healthcare analytics landscape is currently paralyzed by a "Triple Threat" of compounding failures: (1) persistently **Low Analytics Maturity**, where despite decades of investment, only 39 organizations globally, 26 at HIMSS AMAM Stage 6 and 13 at Stage 7, have achieved these maturity levels ([1]); (2) a **Semantic Gap** between clinical intent and technical schema implementation ([2],[3]); and (3) a profound crisis of **Workforce Instability** that creates "Institutional Amnesia" ([4]).

While technical barriers and maturity models are well-documented, the workforce dimension has shifted from a management concern to an existential threat. Modern longitudinal data on analytics staff is fragmented, but the available signals are alarming. As of 2024, 53% of healthcare CIOs have held their roles for less than three years ([5]), creating a strategic vacuum at the top. At the operational level, the situation is equally precarious: 79% of provider organizations report persistent shortages in digital health roles ([6]), and a 2025 study found that 55% of public health informatics specialists intend to leave their positions ([7]).

This turnover creates a phenomenon we define as **Institutional Amnesia**: the systematic erasure of the tacit knowledge required to interpret complex health data. In healthcare, "data" is never raw; it is wrapped in layers of institutional context (billing rules, workflow workarounds, and unwritten exclusions)

(8). When the analyst who knows that "exclusion code 99" actually means "hospice transfer" leaves, that knowledge evaporates. The organization does not just lose an employee; it loses the ability to accurately measure its own performance.

Current literature approaches these problems in isolation. Analytics maturity models (e.g., HIMSS AMAM) assume a stable workforce capable of linear progression (1,9). Technical solutions (e.g., NL2SQL) assume a stable schema and clear intent (10). Neither accounts for the reality of the "Great Resignation," where the rate of knowledge loss ("organizational forgetting") often exceeds the rate of knowledge capture (11).

Traditional knowledge management strategies (wikis, data dictionaries, and documentation) have failed because they are *passive* (12). They require overworked staff to stop working and write down what they know. In a high-burnout environment, this documentation is the first casualty. As a result, healthcare systems are trapped in a Sisyphus-like cycle: hiring new analysts who spend their limited tenure relearning the same institutional secrets, only to leave just as they become productive (13,14). A foundational 2004 study established that healthcare IT staff had the lowest expected tenure among all IT sectors at just 2.9 years (15). That this two-decade-old study remains a key benchmark is itself evidence of the crisis: the industry lacks the stability to track its own attrition. Contemporary signals suggest the situation has worsened, with 30% of new healthcare employees leaving within their first year (16) and 55% of informatics specialists intending to leave their positions (7).

This viewpoint article addresses a critical socio-technical gap: *How can health systems maintain analytics maturity when workforce turnover exceeds the speed of documentation?*

We propose that the solution lies not in better documentation, but in a fundamental architectural shift: moving from *passive* knowledge management to **Human-in-the-Loop Semantic Governance (HiL-SG)**.

2 Theoretical Grounding: SECI and the Unstable Workforce

Using a Design Science Research (DSR) approach, we developed the HiL-SG framework through three steps: (1) a narrative review of the literature (n=139 sources) across healthcare analytics maturity, workforce turnover dynamics, and natural language processing, with grey literature assessed using the AACODS checklist (17); (2) theoretical grounding in Nonaka's SECI model of knowledge creation (18), mapping workforce turnover data to specific failure modes in knowledge transfer; and (3) artifact design of the HiL-SG framework and the "Validated Query Triple" as socio-technical solutions to the identified "Socialization Failure," adhering to "Human-on-the-Loop" principles for AI safety (19).

We ground our approach in Nonaka's SECI Model of knowledge creation (18), which describes organizational knowledge as emerging through a continuous cycle of four conversion modes:

1. **Socialization** (tacit to tacit): Knowledge transfers through shared experience and co-located practice, as when a senior analyst teaches a junior colleague the unwritten rules of a clinical dataset.

2. **Externalization** (tacit to explicit): Individuals articulate tacit know-how into explicit forms such as documents or coded artifacts, as when an analyst records why a specific exclusion code maps to hospice transfers.

3. **Combination** (explicit to explicit): Separately documented knowledge is integrated and systematized into broader structures, as when data dictionary entries are consolidated into a governed analytics catalog.

4. **Internalization** (explicit to tacit): Individuals learn from documented knowledge and convert it into personal expertise through practice, as when a new analyst studies validated query libraries.

In a healthy organization, these four modes form a self-reinforcing spiral: tacit insights become documented, documentation becomes systematized, and systematized knowledge is internalized by new members who then generate fresh tacit insights (18). When any mode breaks down, the spiral stalls. In healthcare analytics, the breakdown is at the very first stage.

2.1 The Broken Cycle: Socialization Failure

In Nonaka's model, **Socialization** is the foundational conversion mode: the primary channel through which newcomers absorb tacit context that formal training cannot convey (18). Socialization depends on two preconditions: sustained interaction and sufficient temporal overlap between knowledge holders and receivers (20). It is, in effect, an apprenticeship model requiring years of shared practice.

In the current healthcare environment, this mechanism has collapsed. The available workforce data reveals an "apprenticeship window" that is shorter than the knowledge transfer cycle it must support. With 53% of healthcare CIOs holding their roles for less than three years (5), strategic knowledge at the leadership level turns over before it can be transmitted. At the operational level, 55% of public health informatics specialists intend to leave their positions (7), and 30% of new employees depart within their first year (16). Meanwhile, specialized informatics roles require 18 to 24 months to reach fluency (13,21). The arithmetic is unforgiving: by the time a new analyst has absorbed enough tacit context to be productive, their mentor may already be gone, and the new analyst is themselves halfway through an average tenure.

High turnover rates fracture the social networks required for mentorship (22,23). The resulting knowledge loss is compounding: each departure removes a node from the organization's informal knowledge network, making subsequent Socialization attempts less effective because fewer experienced practitioners remain to serve as mentors (24). Socialization is no longer a viable strategy for resilience.

2.2 The Solution: Externalization via Socio-Technical Artifacts

To survive, organizations must shift reliance from Socialization to **Externalization**: converting tacit knowledge into explicit, durable artifacts (25). However, traditional Externalization (writing wikis, maintaining data dictionaries, composing runbooks) suffers from two critical weaknesses. First, it is passive: it requires overworked staff to interrupt their workflow and perform a separate documentation task (26). In a high-burnout environment where 79% of provider organizations report persistent shortages in

digital health roles ([6]), this discretionary documentation is the first casualty. Second, it is low-fidelity: the act of writing down tacit knowledge inevitably loses nuance, context, and the conditional logic that makes institutional knowledge valuable ([20]). The result is documentation that exists but does not adequately capture what the departing expert actually knew.

We propose a form of *active* Externalization: one that captures tacit knowledge as a byproduct of the daily workflow of analytics rather than as a separate documentation burden. The mechanism is a new socio-technical artifact: the **Validated Query Triple**. This artifact consists of: 1. **Natural Language Intent**: The clinical business question (e.g., "Hypertension readmissions excluding planned transfers"). 2. **Executable SQL**: The technical implementation. 3. **Rationale Metadata**: The "why" behind the logic (e.g., "Excluding status 02 per CMS 2025 rule").

By capturing these three components *during the act of analytics*, we transform the ephemeral work of query generation into a permanent institutional asset ([27]).

3 Human-in-the-Loop Semantic Governance

We rename the traditional "Validated Query Cycle" to **Human-in-the-Loop Semantic Governance (HiL-SG)** to reflect its role as a governance mechanism rather than just a productivity tool.
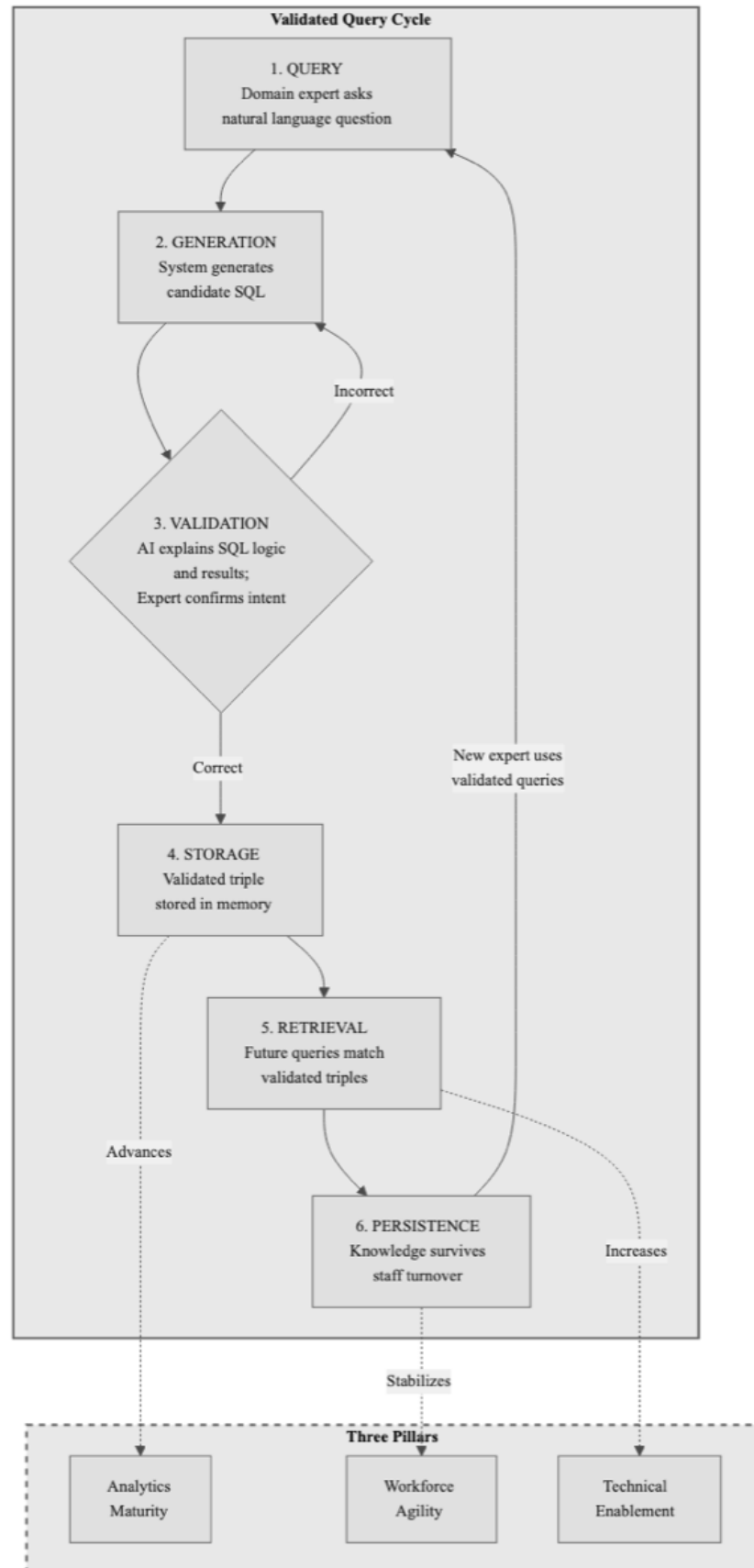
3.1 The HiL-SG Architecture

The HiL-SG architecture (Figure 1) functions as a **Governance Forcing Function**. It inserts a mandatory validation step into the analytics workflow, preventing the "laundering" of hallucinations while simultaneously capturing expert knowledge.

Figure 1: Healthcare Analytics Architecture as a Socio-Technical System. The architecture flows from Clinical Users through a Conversational AI interface to a healthcare NLP engine for context-aware SQL generation. Bi-directional arrows represent the iterative 'Query & Refine' loop. The critical validation step (dotted line) shows domain experts confirming SQL before results flow to 'Organizational Memory' (dashed line), where they persist independent of staff tenure.

The corresponding six step Validated Query Cycle is summarized in Figure 2, which shows how queries move from initial clinical intent through expert validation into durable organizational memory.

Validated Query Cycle

1. QUERY
Domain expert asks
natural language question

2. GENERATION
System generates
candidate SQL

Incorrect

3. VALIDATION
AI explains SQL logic
and results;
Expert confirms intent

Correct

New expert uses
validated queries

4. STORAGE
Validated triple
stored in memory

5. RETRIEVAL
Future queries match
validated triples

Advances

6. PERSISTENCE
Knowledge survives
staff turnover

Increases

Stabilizes

Three Pillars

| Analytics | Workforce | Technical |
| Maturity | Agility | Enablement |

Figure 2: Six step validated query cycle for Human-in-the-Loop Semantic Governance. The cycle progresses from Natural Language Intent to AI-generated SQL, expert review and correction, creation of a Validated Query Triple, storage in organizational memory, and reuse for future queries.

3.2 The Process of Externalization

1. **Query Generation**: A user asks a question. The AI proposes SQL based on schema knowledge (10,28).
2. **Semantic Translation**: The AI translates the SQL back into a natural language explanation (29).
3. **Expert Validation**: The domain expert confirms or corrects this interpretation. *This is the critical moment of Externalization.* This "Human-on-the-Loop" (HotL) step transforms validation into an iterative knowledge capture process (19,30).
4. **Artifact Storage**: The validated triple is hashed and stored in organizational memory (31).
5. **Retrieval**: Future queries semantically match against this repository first, retrieving *trusted* human knowledge before attempting *probabilistic* generation (32).

4 The Evidence Base: Three Pillars

The HiL-SG framework is supported by three pillars of empirical evidence synthesized from over 130 sources.

4.1 Pillar 1: Analytics Maturity Evidence

Healthcare maturity remains chronically low. Assessments reveal only 26 organizations achieved Stage 6 and 13 reached Stage 7 by late 2024 (1,33). Most organizations remain at Stages 0-3, characterized by fragmented data and limited predictive capabilities (34). However, maturity is not merely an IT metric; it is a clinical safety predictor. EMRAM levels 6-7 correlate with 3.25 times higher odds of better Leapfrog Safety Grades (35). Low maturity creates a "low-maturity trap" where data quality issues (such as the 39-71% missing data rates in cancer databases (36)) remain uncorrected because the experts who understand the context are leaving.

Critically, low maturity is not simply a status; it is a self-reinforcing trap. Organizations at Stages 0-3 lack the automated monitoring and data governance infrastructure needed to detect their own deficiencies, creating a vicious cycle in which poor data quality goes unrecognized because no systems exist to measure it. The clinical consequences of this trap are measurable: one Medicare ACO that implemented analytics to overcome EHR fragmentation reduced readmission rates from 24% to 17.8% and achieved $1.6 million in cost savings (37), demonstrating what becomes possible when organizations escape this cycle. Yet 68% of healthcare organizations continue to cite data interoperability as the leading obstacle to analytics adoption, followed by privacy concerns (64%) and insufficient staff training (59%) (38). Barriers including employee resistance to change and lack of organizational readiness further stall data-driven initiatives (39,40). The low-maturity trap thus compounds over time: each year of delayed investment widens the gap between what the organization could know and what it actually knows.

4.2 Pillar 2: Workforce Agility Evidence

The cost of turnover in informatics is higher than standard IT. Knowledge loss can cost up to three times annual salary (24,41). With 30% of new employees leaving within their first year (16), healthcare IT professionals spend a limited portion of their employment at full productivity, as specialized roles require 18-24 months to reach fluency (13,21). This "revolving door" prevents the accumulation of the "Collective Knowledge Structures" required for complex task performance (11).

The workforce crisis operates at multiple reinforcing levels. At the strategic level, 53% of healthcare CIOs have tenures of less than three years (5), producing recurring shifts in analytics strategy that destabilize long-term initiatives. At the operational level, 79% of provider organizations report persistent shortages in digital health roles (6). At the foundational level, 55% of public health informatics specialists intend to leave their positions (7), draining the specialized talent needed to maintain analytics infrastructure. This multi-level instability directly undermines the SECI Socialization mode discussed in the Theoretical Grounding section: sustained mentorship requires temporal overlap between experienced practitioners and newcomers, yet the revolving door at every organizational tier ensures that overlap rarely materializes. A foundational 2004 study established that healthcare IT staff had the lowest expected tenure for new hires among all IT sectors at just 2.9 years (15). That this two-decade-old benchmark remains a primary reference point is itself evidence of the crisis: the field has lacked the stability even to systematically track its own attrition over the intervening decades.

4.3 Pillar 3: Technical Enablement Evidence

NL2SQL has reached a productivity tipping point. Natural language interfaces report a 63% increase in self-service adoption and 37% reduction in retrieval time (42). Precision medicine platforms achieve 92.5% accuracy in parsing complex queries (43). While current models are "not yet sufficiently accurate for unsupervised use" (29), domain-adapted systems like MedT5SQL reach 80% accuracy on benchmarks (44). These tools function as the "externalization engine" required for the HiL-SG framework.

However, NL2SQL is an enabler, not a solution in itself. Its deeper significance lies in the organizational prerequisites it demands. For an AI system to translate a natural language question into a correct SQL query, the organization must first establish validated data models, explicit business logic definitions, and codified domain terminology (2,3). In other words, the technology forces organizational discipline as a precondition for functioning, making it a governance forcing function even before considering the query results. This reframes NL2SQL from a convenience tool into a catalyst for the kind of systematic knowledge externalization that the HiL-SG framework requires. The interface bridges the semantic gap between clinical experts and technical schema, allowing non-technical domain experts to interact with data alongside broader modernization efforts (45–48). The technical barrier thus becomes, paradoxically, a governance opportunity: the very difficulty of making NL2SQL work correctly compels organizations to surface and formalize the tacit knowledge that would otherwise remain trapped in departing experts.

5 The Analytics Resilience Index

To measure success, we propose the **Analytics Resilience Index (ARI)**, replacing static checklists with dynamic resilience metrics.

5.1 Why Resilience, Not Maturity

Existing maturity models such as the HIMSS Analytics Maturity Assessment Model (AMAM) assume linear progression through discrete stages and implicitly presuppose a stable workforce capable of sustaining each level once achieved (1,9). In practice, this assumption is violated routinely. An organization that reaches AMAM Stage 5 but regresses to Stage 3 after the departure of two senior analysts has not failed to mature; it has failed to be *resilient*. Static maturity scores capture a snapshot of peak capability but reveal nothing about the organization's ability to sustain that capability through disruption. The ARI addresses this gap by shifting the measurement focus from "where you are" to "how far you fall when someone leaves."

5.2 Operationalizing the ARI

Each ARI dimension (Table 1) can be scored on a Likert-type scale from 1 (fragile) to 5 (antifragile). For example, the "Knowledge Locus" dimension would be scored by surveying whether key analytical queries are documented in a shared, version-controlled repository (score 5) or known only to named individuals who could leave at any time (score 1). Similarly, "Turnover Impact" could be assessed through scenario exercises that simulate the departure of a critical team member and measure the time required to restore reporting capability. An aggregate ARI score across all dimensions provides a composite indicator of organizational resilience posture, enabling longitudinal tracking and cross-institutional benchmarking.

Critically, the ARI complements rather than replaces AMAM. Where AMAM measures the sophistication of an organization's analytical capabilities at a point in time, the ARI measures the durability of those capabilities under workforce stress. An organization should aspire to high scores on both instruments: AMAM for capability and ARI for sustainability. Used together, they provide a two-dimensional view of analytics health that neither instrument offers alone.

Table 1: The Analytics Resilience Index (ARI).

Dimension	Low Resilience (Fragile)	High Resilience (Antifragile)	Evidence
Knowledge Locus	Knowledge resides in "Hero" analysts.	Knowledge resides in the System/Repository.	(4,31)

Dimension	Low Resilience (Fragile)	High Resilience (Antifragile)	Evidence
Turnover Impact	Departure of 1 staff member stops reporting.	Departure causes minimal disruption; successors inherit queries.	(11,24)
Validation Mode	Ad-hoc, email-based, ephemeral.	Systematic, artifact-based, durable (HiL-SG).	(27,30)
Schema Coupling	Hard-coded reports break on schema change.	Semantic layer adapts; CI/CD detects drift.	(49,50)

6 The Validator Paradox and Standard Work

A critical objection to HiL-SG is circular: if the framework requires domain experts to validate AI-generated queries, and the core problem is that domain experts are leaving, then the framework fails precisely when it is most needed. This **Validator Paradox** represents the strongest counterargument to the approach proposed here, and addressing it requires moving beyond simplistic reassurance.

The resolution draws on Lean management's concept of "Standard Work" (51). In this framing, validation is not the establishment of *eternal truth* but the documentation of the *current known standard*. Each time an analyst validates a query triple, they record the best available understanding of how a business question maps to a data operation at that moment in time. The validation is time-stamped and contextual, not permanent. Critically, as Alukal and Manos (51) establish, standard work is the prerequisite for Kaizen (continuous improvement): without a documented baseline, there is no foundation to improve upon. Each validated query therefore establishes a floor, not a ceiling. When the next expert arrives (whether a seasoned veteran or a competent mid-career hire), they inherit a baseline and can refine it rather than reconstructing institutional knowledge from scratch.

This mechanism functions as a **Knowledge Ratchet** (11). Each validated triple prevents regression below the last confirmed state. Even if a subsequent validator is less experienced than their predecessor, the organization cannot slide below the previously validated standard. The analogy to version control is instructive: each commit in a software repository preserves a known-good state, and future contributors can build upon it even if they occasionally introduce errors. The ratchet does not guarantee forward progress, but it does prevent catastrophic backsliding, which is the central failure mode of institutional amnesia.

Real-world evidence supports this mechanism. UC Davis Health moved from AMAM Stage 0 to Stage 6 by establishing standardized "S.M.A.R.T." definitions for its analytics metrics (52). Those codified standards survived staff turnover precisely because they existed as organizational artifacts rather than as

knowledge held solely by the individuals who created them. The HiL-SG validated query library serves an analogous function: it encodes analytical decisions into durable, retrievable structures that persist independent of any single analyst's tenure.

However, the Validator Paradox is not fully resolved. There exists a minimum viable expertise threshold below which validation becomes meaningless. A junior analyst rubber-stamping AI-generated output without genuine comprehension provides no knowledge ratchet; the validation artifact exists, but its epistemic value is nil. Identifying this threshold, and understanding how organizational factors (training, supervision, query complexity) influence it, remains an open empirical question. Future work in this series (Paper 2) should measure this threshold via controlled hallucination injection studies, in which AI-generated queries containing deliberate errors are presented to validators of varying experience levels to determine the conditions under which validation ceases to be meaningful.

7 Safety as Cognitive Forcing

HiL-SG is fundamentally a **safety mechanism**, not a productivity tool. The central risk of unsupervised AI in clinical analytics is what we term "laundering hallucinations": a plausible-sounding but factually incorrect query result that enters the decision pipeline undetected and influences clinical or operational choices. Because large language models generate fluent, confident output regardless of correctness, the absence of a structured validation step means that errors arrive dressed in the language of expertise, making them harder to catch than obviously malformed output.

HiL-SG mitigates this risk through **Cognitive Forcing Functions** (29), a design pattern borrowed from clinical decision-making and safety engineering. By requiring the AI to explain its reasoning *before* presenting results, the architecture forces the human validator into System 2 (analytical, deliberate) thinking rather than allowing System 1 (fast, heuristic) acceptance of superficially plausible output. User studies confirm the practical benefit: structured explanation reduces error recovery time by 30 to 40 seconds compared to unstructured output review (53).

The parallel to aviation safety is instructive. Checklists and mandatory call-outs transformed commercial aviation from a high-risk endeavor into one of the safest modes of transportation, not by eliminating human error but by creating procedural structures that surface errors before they propagate. HiL-SG applies the same principle to analytics: the mandatory validation step functions as an analytical "call-out" that interrupts the default path of uncritical acceptance. In this framing, the friction introduced by validation is not a cost; it is the mechanism of safety itself.

8 Structural Barriers: Why the Problem Persists

Failed standardization approaches (e.g., IBM Watson Health (54,55), Haven (56,57)) demonstrate that centralized models fail clinical reality. Metadata uncertainties and "messy" institution-specific business logic require localized solutions (2,58). HiL-SG addresses this by capturing *local* logic rather than enforcing *global* standards.

9 Limitations

This work is a narrative, design science informed framework rather than a systematic review or multi-site empirical evaluation. The literature base is concentrated on English-language sources and recent (2024–2025) workforce and NL2SQL studies, so findings may not capture all regional, specialty-specific, or technological contexts. The HiL-SG architecture and the proposed Analytics Resilience Index (ARI) are conceptual artifacts that require future implementation and validation in diverse health systems before their effectiveness and generalizability can be fully established.

10 Implications and Future Research

The crisis of Institutional Amnesia in healthcare requires a structural shift. As long as analytical maturity is tied to individual tenure, organizations will remain fragile. By implementing **Human-in-the-Loop Semantic Governance**, health systems can decouple intelligence from turnover, building a library of validated knowledge that ensures maturity advances even as the workforce evolves.

Future research should empirically validate and refine the HiL-SG framework and the proposed Analytics Resilience Index. Priority questions include: how ARI scores correlate with observed continuity of analytics performance during leadership and staff turnover; whether HiL-SG mediated natural language to SQL workflows reduce error rates, recovery time, and rework compared to baseline tooling; and which governance patterns most effectively balance safety, transparency, and equity when human validators operate at scale. Prospective multi-site implementation studies, controlled user experiments, and qualitative implementation research across diverse health systems will be needed to test these claims and adapt the framework to varying organizational, regulatory, and data environments.

11 Acknowledgments

The author (S.T.H.) takes full responsibility for the final content, conducted the research, and verified all claims and citations. Gemini CLI (Gemini 3, Google) assisted with manuscript editing and refinement. Figures were generated using the Mermaid graph language.

12 Author Contributions

S.T.H. conceived the research, conducted the literature review, and wrote the manuscript.

13 Conflicts of Interest

The author declares the following competing interests: Samuel T Harrold is a contract product advisor at Yuimedi, Inc., which develops healthcare analytics software including conversational AI platforms relevant to this review's subject matter. The author is also employed as a Data Scientist at Indiana University Health. This paper presents an analytical framework derived from published literature and does not evaluate or recommend specific commercial products, including those of the author's affiliated organizations. The views expressed are the author's own and do not represent the official positions of Indiana University Health or Yuimedi, Inc.

14 Data Availability

This is a narrative review synthesizing existing literature. No primary datasets were generated or analyzed. All data cited are from publicly available peer-reviewed publications and industry reports, referenced in the bibliography.

15 Funding

16 Abbreviations

AACODS: Authority, Accuracy, Coverage, Objectivity, Date, Significance AI: Artificial Intelligence AMAM: Analytics Maturity Assessment Model ARI: Analytics Resilience Index CIO: Chief Information Officer DSR: Design Science Research EMRAM: Electronic Medical Record Adoption Model HiL-SG: Human-in-the-Loop Semantic Governance HIMSS: Healthcare Information Management Systems Society HotL: Human-on-the-Loop IT: Information Technology NL2SQL: Natural Language to SQL SECI: Socialization, Externalization, Combination, Internalization SQL: Structured Query Language

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