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

Samuel T Harrold, Yuimedi, Inc.

January 2026

Background: Healthcare organizations face a "Triple Threat" of low analytics maturity, high workforce instability, and semantic technical barriers. Recent data reveals a crisis of "Institutional Amnesia," where 53% of healthcare CIOs have less than three years' tenure and 55% of informatics specialists intend to leave their roles. This churn erases the tacit knowledge required to navigate complex clinical data schemas, trapping organizations in a cycle of low maturity.

Objective: This article proposes a socio-technical framework to mitigate institutional amnesia by decoupling organizational analytical capability from individual staff tenure. We aim to answer the research question: *How can health systems maintain analytics maturity when workforce turnover exceeds the speed of documentation?*

Methods: We employed a Design Science Research (DSR) approach, synthesizing evidence from healthcare informatics, knowledge management, and natural language processing. The framework is grounded in Nonaka's SECI model of knowledge creation, reinterpreting "Socialization" vulnerabilities through the lens of workforce turnover data (2024-2025).

Results: We present the "Human-in-the-Loop Semantic Governance" (HiL-SG) framework. This architecture functions as a socio-technical artifact that converts tacit domain expertise into explicit, executable "Validated Query Triples" (Natural Language + SQL + Rationale). By shifting the locus of knowledge from volatile human memory to durable semantic artifacts, the framework enables an "Analytics Resilience Index" (ARI) that measures an organization's ability to sustain insights despite staff churn.

Conclusions: The "Validator Paradox"—who validates the AI when experts leave?—is resolved by treating validation as "standard work" rather than eternal truth. By embedding knowledge capture into the daily workflow of query generation, healthcare systems can build a "knowledge ratchet" that prevents the regression of capabilities, ensuring that analytics maturity advances even as the workforce evolves.

Contents

1 Introduction

1.1 The Triple Threat: A Crisis of Institutional Amnesia

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 have achieved HIMSS AMAM Stage 6-7 (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.

1.2 Gap Analysis: The Speed of Forgetting

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 average 2.9-year tenure (13) relearning the same institutional secrets, only to leave just as they become productive (14,15).

1.3 Research Question

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 Methods

We employed a Design Science Research (DSR) approach to develop the HiL-SG framework. DSR involves the creation and evaluation of innovative artifacts (constructs, models, methods, and instantiations) to solve identified organizational problems.

Our methodology followed three steps: 1. **Problem Identification**: We conducted a narrative review of the literature (n=139 sources) across three domains: healthcare analytics maturity, workforce turnover dynamics, and natural language processing. Grey literature was assessed using the AACODS checklist (16). 2. **Theoretical Grounding**: We analyzed the identified problem ("Institutional Amnesia") through the lens of Nonaka's SECI model of knowledge creation (17), mapping workforce turnover data to specific failure modes in knowledge transfer. 3. **Artifact Design**: We designed the HiL-SG framework and the "Validated Query Triple" artifact as socio-technical solutions to the identified "Socialization Failure," adhering to "Human-on-the-Loop" principles for AI safety (18).

3 Results

3.1 Theoretical Framework: SECI for the Unstable Workforce

We ground our approach in Nonaka's SECI Model of knowledge creation (Socialization, Externalization, Combination, Internalization), reinterpreted for the crisis of the modern healthcare workforce.

3.1.1 The Broken Cycle: Socialization Failure

In Nonaka's model, **Socialization** is the transfer of tacit knowledge (experience, context) between individuals through shared experience (17). In the current healthcare environment, this mechanism has collapsed. High turnover rates fracture the social networks required for mentorship (19,20). When a senior analyst leaves every 3 years, the "apprenticeship" model of informatics breaks down. Socialization is no longer a viable strategy for resilience (21).

3.1.2 The Solution: Externalization via Socio-Technical Artifacts

To survive, organizations must shift reliance from Socialization to **Externalization**: converting tacit knowledge into explicit, durable artifacts (22). However, traditional externalization (writing reports) is too slow and low-fidelity (23,24).

We propose 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 (25).

3.2 Human-in-the-Loop Semantic Governance (HiL-SG)

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.

3.2.1 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.

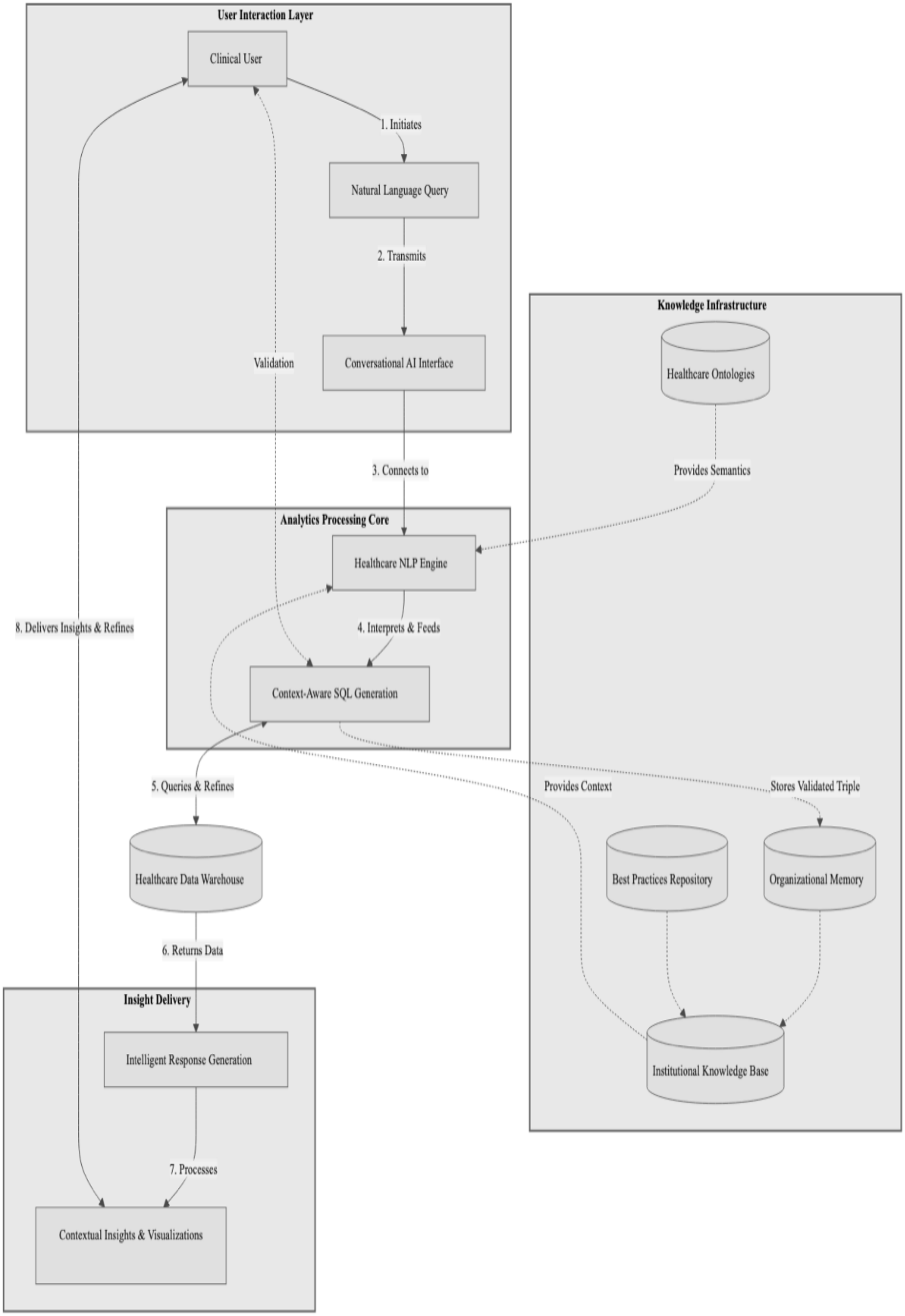

Figure 1: Healthcare Analytics Architecture as a Socio-Technical System. The architecture flows from Clinical Users through a Conversational AI interface to a healthcare NLP engine for context-aware SQL generation. Bi-directional arrows represent the iterative 'Query & Refine' loop. The critical validation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

3.2.2 The Process of Externalization

1. **Query Generation**: A user asks a question. The AI proposes SQL based on schema knowledge (10,26).
2. **Semantic Translation**: The AI translates the SQL back into a natural language explanation (27).
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 (18,28).
4. **Artifact Storage**: The validated triple is hashed and stored in organizational memory (29).
5. **Retrieval**: Future queries semantically match against this repository first, retrieving *trusted* human knowledge before attempting *probabilistic* generation (30).

3.3 Empirical Grounding: The Evidence Base

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

3.3.1 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 (1,31). Most organizations remain at Stages 0-3, characterized by fragmented data and limited predictive capabilities (32). 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 (33). Low maturity creates a "low-maturity trap" where data quality issues—such as the 39-71% missing data rates in cancer databases (34)—remain uncorrected because the experts who understand the context are leaving.

3.3.2 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 (21,35). With 30% of new employees leaving within their first year (36), healthcare IT professionals spend a limited portion of their employment at full productivity, as specialized roles require 18-24 months to reach fluency (14,37). This "revolving door" prevents the accumulation of the "Collective Knowledge Structures" required for complex task performance (11).

3.3.3 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 (38). Precision medicine platforms achieve 92.5% accuracy in parsing complex queries (39). While current models are "not yet sufficiently accurate for unsupervised use" (27), domain-adapted systems like MedT5SQL reach 80% accuracy on benchmarks (40). These tools function as the "externalization engine" required for the HiL-SG framework.

3.4 Analytics Resilience Index (ARI)

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

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.	(4,29)
Turnover Impact	Departure of 1 staff member stops reporting.	Departure causes minimal disruption; successors inherit queries.	(11,21)
Validation Mode	Ad-hoc, email-based, ephemeral.	Systematic, artifact-based, durable (HiL-SG).	(25,28)
Schema Coupling	Hard-coded reports break on schema change.	Semantic layer adapts; CI/CD detects drift.	(41,42)

4 Discussion

4.1 The Validator Paradox and Standard Work

A critical criticism of HiL-SG is the **Validator Paradox**: *If the experts are leaving, who is left to validate the AI?* We resolve this by reframing validation through Lean "Standard Work" (43). Validation is the establishment of the *current known standard*. When an analyst validates a query, they act as a **Knowledge Ratchet** (11), preventing the organization from sliding back to zero. This aligns with UC Davis Health's success in moving from AMAM Stage 0 to 6 by establishing standardized "S.M.A.R.T." definitions (44).

4.2 Safety: Cognitive Forcing Functions

Automating analytics risks "laundering hallucinations." HiL-SG mitigates this via **Cognitive Forcing Functions** (27). By requiring AI to explain logic *before* results, we force the user to engage analytical thinking. User studies show this reduces error recovery time by 30-40 seconds (45).

4.3 Structural Barriers: Why the Problem Persists

Failed standardization approaches (e.g., IBM Watson Health (46,47), Haven (48,49)) demonstrate that centralized models fail clinical reality. Metadata uncertainties and “messy” institution-specific business logic require localized solutions (2,50). HiL-SG addresses this by capturing *local* logic rather than enforcing *global* standards.

5 Conclusion

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.

6 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.

7 Author Contributions

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

8 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.

9 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.

10 Funding

Yuimedi provided funding for the author's time writing and researching this manuscript.

11 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

12 References

1. Analytics H. Analytics maturity assessment model (AMAM) global report. Healthcare Information and Management Systems Society [Internet]. HIMSS Analytics; 2024. Available from: https://www.himss.org/maturity-models/amam/

2. Gal MS, Rubinfeld DL. Data Standardization. NYU Law Review [Internet]. 2019;94(4):737–70. Available from: https://www.nyulawreview.org/issues/volume-94-number-4/data-standardization/

3. Zhang Y, Callaghan-Koru JA, Koru G. The challenges and opportunities of continuous data quality improvement for healthcare administration data. JAMIA Open. 2024;7(2):ooae042.

4. Hong JH. When does employee turnover matter? Organizational memory in federal IT. Journal of Public Administration Research and Theory [Internet]. 2025; Available from: https://academic.oup.com/jpart/advance-article-abstract/doi/10.1093/jopart/muaf019/8162522

5. WittKieffer. CIO Insights: The State of Healthcare IT Leadership [Internet]. WittKieffer; 2024. Available from: https://api.wittkieffer.com/wp-content/uploads/2012/10/cio-insights-the-state-of-healthcare-it-leadership-wittkieffer-october-2024.pdf

6. HIMSS. The Future of Workforce [Internet]. Healthcare Information; Management Systems Society; 2024. Available from: https://www.himss.org/resources/the-future-of-workforce/

7. Rajamani L S. Public health informatics specialists in state and local public health workforce: Insights from public health workforce interests and needs survey. Journal of Public Health Management and Practice [Internet]. 2025; Available from: https://academic.oup.com/jpubhealth

8. NORC at the University of Chicago AHIMA &. Health information workforce survey report [Internet]. American Health Information Management Association & NORC at the University of Chicago; 2023. Available from: https://www.ahima.org/news-publications/press-room-press-releases/2023-press-releases/health-information-workforce-shortages-persist-as-ai-shows-promise-ahima-survey-reveals/

9. Wang K Y., Byrd TA. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. Technological Forecasting and Social Change [Internet]. 2018;126:3–13. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0040162516000500

10. Wang S P. Text-to-SQL generation for question answering on electronic medical records. In: Proceedings of the web conference 2020 [Internet]. 2020. Available from: https://arxiv.org/abs/1908.01839

11. Rao RD, Argote L. Organizational learning and forgetting: The effects of turnover and structure. European Management Review [Internet]. 2006;3(2):77–85. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1057/palgrave.emr.1500057

12. Mayo D C. S. How can we effect culture change toward data-driven medicine? International Journal of Radiation Oncology, Biology, Physics [Internet]. 2016; Available from: https://www.redjournal.org/article/S0360-3016(16)00260-1/fulltext

13. Ang &S S. Turnover of information technology professionals: The effects of internal labor market strategies. ACM SIGMIS Database: The DATABASE for Advances in Information Systems [Internet]. 2004; Available from: https://dl.acm.org/doi/10.1145/1017114.1017118

14. Ledikwe R J. H. Establishing a health information workforce: Innovation for low- and middle-income countries. Human Resources for Health [Internet]. 2013; Available from: https://human-resources-health.biomedcentral.com/articles/10.1186/1478-4491-11-35

15. Mantas A J. Recommendations of the International Medical Informatics Association (IMIA) on education in biomedical and health informatics: First revision. Methods of Information in Medicine [Internet]. 2010; Available from: https://pubmed.ncbi.nlm.nih.gov/20054502/

16. Tyndall J. AACODS Checklist. Flinders University [Internet]. 2010. Available from: https://dspace.flinders.edu.au/jspui/bitstream/2328/3326/4/AACODS_Checklist.pdf

17. Farnese B M. L. Managing knowledge in organizations: A Nonaka's SECI model operationalization. Frontiers in Psychology [Internet]. 2019; Available from: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02730

18. Bravo Rocca GJ. Human-on-the-loop continual learning [Internet] [PhD thesis]. Universitat Politècnica de Catalunya; 2023. Available from: https://www.tdx.cat/bitstream/handle/10803/695722/TGJBR1de1.pdf?sequence=1

19. Wu L F., Li L. Worldwide prevalence and associated factors of nursing staff turnover: A systematic review and meta-analysis. Nursing Open [Internet]. 2024;11:e2097. Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC10802134/

20. Ren W L. Global prevalence of nurse turnover rates: A meta-analysis of 21 studies from 14 countries. Journal of Nursing Management [Internet]. 2024; Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC11919231/

21. Massingham PR. Measuring the impact of knowledge loss: A longitudinal study. Journal of Knowledge Management [Internet]. 2018; Available from: https://doi.org/10.1108/JKM-08-2016-0338

22. Zhang D W. AI challenges conventional knowledge management: Light the way for reframing SECI model and Ba theory. Journal of Knowledge Management [Internet]. 2025; Available from: https://www.emerald.com/insight/content/doi/10.1108/JKM-03-2024-0262/full/html

23. Goffin &K K. Tacit knowledge, lessons learnt, and new product development. Journal of Product Innovation Management [Internet]. 2011; Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-5885.2010.00798.x

24. Foos S T. Tacit knowledge transfer and the knowledge disconnect. Journal of Knowledge Management [Internet]. 2006; Available from: https://www.emerald.com/insight/content/doi/10.1108/13673270610650067/full/html

25. Moore D et al. ActiveNavigator: Toward real-time knowledge capture and feedback in active learning spaces. International Journal of Engineering Education [Internet]. 2018;34(2):1–12. Available from: https://wendyju.com/publications/18_ijee3593.pdf

26. Lee et al G. EHRSQL: A practical text-to-SQL benchmark for electronic health records. In: Proceedings of NeurIPS 2022 [Internet]. 2023. Available from: https://arxiv.org/abs/2301.07695

27. Ziletti &D A. Retrieval augmented text-to-SQL generation for epidemiological question answering using electronic health records. NAACL 2024 Clinical NLP Workshop [Internet]. 2024; Available from: https://arxiv.org/abs/2403.09226

28. Mosqueira-Rey E et al. Human-in-the-loop machine learning: A state of the art. Artificial Intelligence Review [Internet]. 2023;56:3005–54. Available from: https://link.springer.com/content/pdf/10.1007/s10462-022-10246-w.pdf

29. Benbya P H. Corporate portal: A tool for knowledge management synchronization. International Journal of Information Management [Internet]. 2004; Available from: https://doi.org/10.1016/j.ijinfomgt.2003.12.012

30. Whittaker S, Hyland P, Wiley M. Design and evaluation of systems to support interaction capture and retrieval. Personal and Ubiquitous Computing [Internet]. 2008;12(3):197–209. Available from: https://www.academia.edu/download/41283190/Design_and_evaluation_of_systems_to_supp20160117-25708-98zc50.pdf

31. Healthcare IT News. HIMSS launches modernised Analytics Maturity Assessment Model [Internet]. 2024. Available from: https://www.healthcareitnews.com/news/asia/himss24-apac-adoption-model-analytics-maturity-gets-facelift

32. Catalyst H. The healthcare analytics adoption model: A roadmap to analytic maturity [Internet]. 2020. Available from: https://www.healthcatalyst.com/learn/insights/healthcare-analytics-adoption-model-roadmap-analytic-maturity

33. Snowdon H A., Wright A. Digital maturity as a predictor of quality and safety outcomes in US hospitals: Cross-sectional observational study. Journal of Medical Internet Research [Internet]. 2024;26:e56316. Available from: https://www.jmir.org/2024/1/e56316

34. Yang DX, Khera R, Miccio JA, Jairam V, et al. Prevalence of missing data in the national cancer database and association with overall survival. JAMA Network Open [Internet]. 2021;4(3):e211793. Available from: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2777777

35. Oracle. The real cost of turnover in healthcare [Internet]. 2024. Available from: https://www.oracle.com/human-capital-management/cost-employee-turnover-healthcare/

36. NSI Nursing Solutions. 2025 National Health Care Retention & RN Staffing Report [Internet]. NSI Nursing Solutions; 2024. Available from: https://www.nsinursingsolutions.com/documents/library/nsi_national_health_care_retention_report.pdf

37. Konrad &S I. Exploring the potential of an IT capability in its bootstrap phase from a task driven onboarding perspective: Insights toward information infrastructure in healthcare [Internet] [Master's thesis]. 2022. Available from: https://www.diva-portal.org/smash/record.jsf?pid=diva2:1684142

38. Dadi CB, Hoque MR, Ali MM, Ferdausi S, Fatema K, Hasan MR. Natural Language Interfaces for Database Management: Bridging the Gap Between Users and Data through Conversational AI. Journal of Computer Science and Technology Studies [Internet]. 2025;7(3):927–33. Available from: https://al-kindipublisher.com/index.php/jcsts/article/view/9694

39. Yang EW, Waldrup B, et al. Conversational Artificial Intelligence for Integrating Social Determinants, Genomics, and Clinical Data in Precision Medicine: Development and Evaluation. JMIR Bioinformatics and Digital Health [Internet]. 2025; Available from: https://bioinform.jmir.org/2025/1/e63139

40. Marshan A A. MedT5SQL: a transformers-based large language model for text-to-SQL conversion in the healthcare domain. Frontiers in Big Data [Internet]. 2024; Available from: https://www.frontiersin.org/articles/10.3389/fdata.2024.1371680

41. Mannapur S. Understanding data drift and concept drift in machine learning systems. International Journal of Scientific Research [Internet]. 2025; Available from: https://www.quantbeckman.com/api/v1/file/5b240742-bf0d-4f8c-a0f9-cb29fab42611.pdf

42. Battula SKY. Adaptive Data Quality Management for Multi-Cloud Healthcare Warehouses: FHIR-Aware Semantics and Unsupervised Thresholding. International Journal of Artificial Intelligence, Data Science, and Machine Learning. 2025;6(4):218–26.

43. Alukal VG, Manos A. Lean kaizen: A simplified approach to process improvement [Internet]. Milwaukee, WI: ASQ Quality Press; 2006. Available from: https://books.google.com/books?id=9uqiEAAAQBAJ

44. HIMSS. UC Davis Health: From Stage 0 to AI Heroes [Internet]. Healthcare Information; Management Systems Society; 2025. Available from: https://pages.himss.org/LP-HA-Case-Study-UC-Davis.html

45. Ipeirotis &Z P. Natural Language Interfaces for Databases: What Do Users Think? arXiv preprint arXiv:251114718 [Internet]. 2025; Available from: https://arxiv.org/abs/2511.14718

46. IBM. Francisco Partners to Acquire IBM's Healthcare Data and Analytics Assets. IBM Newsroom [Internet]. 2022; Available from: https://newsroom.ibm.com/2022-01-21-Francisco-Partners-to-Acquire-IBMs-Healthcare-Data-and-Analytics-Assets

47. Strickland E. IBM Watson, heal thyself: How IBM overpromised and underdelivered on AI health care. IEEE Spectrum [Internet]. 2019;56(4):24–31. Available from: https://ieeexplore.ieee.org/abstract/document/8678513/

48. LaVito A. Haven, the Amazon-Berkshire-JPMorgan venture to disrupt healthcare, is disbanding after 3 years. CNBC [Internet]. 2021; Available from: https://www.cnbc.com/2021/01/04/haven-the-amazon-berkshire-jpmorgan-venture-to-disrupt-healthcare-is-disbanding-after-3-years.html

49. Acchiardo JM, Gunderman RB. The Failure of Haven Healthcare: Lessons for Radiology Learners. Academic Radiology [Internet]. 2021;28(7):1036–7. Available from: https://www.academicradiology.org/article/S1076-6332(21)00140-9/abstract

50. Yang J, Chesbrough H, Hurmelinna-Laukkanen P. The rise, fall, and resurrection of IBM Watson Health [Internet]. University of Oulu; 2020. Available from: https://oulurepo.oulu.fi/bitstream/handle/10024/27921/nbnfi-fe2020050424858.pdf