Healthcare Analytics Challenges: A Three-Pillar Framework Connecting Analytics Maturity, Workforce Agility, and Technical Enablement

Samuel T Harrold, Yuimedi, Inc.

January 2026

Background: Healthcare organizations face three interconnected challenges: low analytics maturity, with only 39 organizations globally having achieved HIMSS AMAM Stage 6-7; systemic instability from high leadership turnover (53% of CIOs with <3 years tenure) and persistent digital skills shortages; and technical barriers in natural language to SQL generation. When these challenges interact, they create institutional memory loss that threatens data-driven healthcare transformation.

Objective: This research develops a three-pillar analytical framework connecting analytics maturity, workforce agility, and technical enablement. The framework reveals how these capabilities interconnect and compound each other.

Methods: We conducted a narrative literature review of peer-reviewed studies and industry reports on natural language to SQL (NL2SQL) generation, healthcare analytics maturity, and workforce turnover. Grey literature was assessed using the AACODS checklist. Evidence was synthesized through the three-pillar analytical framework to examine how these challenges interconnect and compound.

Results: Healthcare-specific text-to-SQL benchmarks show significant progress, though current models are "not yet sufficiently accurate for unsupervised use" in clinical settings. Most healthcare organizations remain at HIMSS AMAM Stages 0-3 with limited predictive capabilities. Healthcare IT turnover significantly exceeds other IT sectors, creating measurable institutional memory loss. The framework reveals a compounding dynamic: low-maturity organizations experience higher turnover, which degrades the institutional knowledge needed for maturity advancement, while technical barriers prevent the capture of expertise before it is lost.

Conclusions: We contribute a three-pillar analytical framework synthesizing evidence on analytics maturity, workforce agility, and technical enablement. The framework reveals a compounding effect: low maturity accelerates turnover, which degrades maturity, and low enablement prevents recovery. This analytical lens enables organizational self-assessment and informs future research on technological interventions, such as conversational AI platforms.

Contents

1 Introduction

Healthcare organizations face three interconnected challenges that collectively threaten their data-driven transformation. Unlike technology or financial services, healthcare combines complex clinical workflows, extensive regulatory requirements, and a workforce with limited technical training but deep domain expertise (1). This paper introduces a three-pillar framework connecting analytics maturity, workforce agility, and technical enablement.

The framework components reveal a compounding crisis. First, analytics maturity remains low: only 39 organizations globally have achieved HIMSS AMAM Stage 6 or 7, with the vast majority remaining at Stages 0-3 (2,3). Second, workforce instability accelerates this stagnation: 53% of healthcare CIOs leave within three years, and widespread digital skills shortages prevent the accumulation of institutional knowledge (4–6). Third, technical barriers: specifically the "semantic gap" between clinical questions and SQL databases - create a dependency on specialized staff who are prone to turnover (7,8).

Theoretical grounding for this framework aligns with the Data-Information-Knowledge-Wisdom (DIKW) hierarchy and knowledge management theory. Pillar 1 (Analytics Maturity) maps to the Data-to-Information transition (2,9). Pillar 2 (Workforce Agility) ensures the retention of Tacit Knowledge required for wisdom (10–12). Pillar 3 (Technical Enablement) facilitates Knowledge Codification, converting ephemeral expertise into durable systems (13,14). Root cause analysis (RCA) methodology determined the framework's ordering: low maturity (Observation) is driven by workforce instability (Cause), which is exacerbated by technical barriers (Mechanism) (15,16).

The framework reveals that these are not isolated problems but a single compounding cycle. Low maturity increases reliance on manual "heroics," leading to burnout and turnover. High turnover erodes the institutional memory needed to build mature systems. Technical barriers prevent the capture of expertise before staff depart. When these barriers are addressed, outcomes improve: one Medicare ACO reduced readmission rates from 24% to 17.8% and saved $1.6 million by overcoming data fragmentation (17). Conversely, 68% of organizations cite interoperability as a leading obstacle to such improvements (18–20).

1.1 Contributions

This paper makes three contributions to the healthcare informatics literature:

1. **Three-Pillar Analytical Framework:** We synthesize evidence to reveal how low maturity, workforce instability, and technical barriers compound each other.
2. **Evidence Synthesis:** We provide a comprehensive review of analytics maturity benchmarks, turnover impacts, and NL2SQL capabilities (21,22).
3. **Validated Query Cycle:** We describe an architectural pattern for "continuous analytic integration" that captures institutional memory, ensuring knowledge persists independently of staff tenure.

2 Methodology

We conducted a narrative literature review to synthesize evidence across analytics maturity, workforce agility, and technical enablement. Literature was identified between January 2023 and December 2025 via Crossref, PubMed, arXiv, and Semantic Scholar (n=570). Sources included peer-reviewed studies in clinical informatics and NLP, alongside industry reports from HIMSS, AHIMA, and technology vendors. Screening for relevance and attribution reduced the corpus to 135 sources (115 academic, 20 industry).

Grey literature was assessed using the AACODS checklist (Authority, Accuracy, Coverage, Objectivity, Date, Significance) to ensure rigor (23). High-authority sources such as HIMSS standards and NHS Trust case studies were prioritized (2,24,25). Vendor-sponsored reports were retained only when filling specific data gaps (e.g., salary-linked turnover costs) and are explicitly flagged (26–28). This approach integrates diverse evidence types - from benchmark datasets to workforce surveys - to construct a coherent framework for interconnected challenges.

3 Framework Development and Evidence

This section presents the Three-Pillar Framework, synthesizing evidence from the literature review to validate each dimension.

3.1 Pillar 1: Analytics Maturity

The Healthcare Information Management Systems Society (HIMSS) Analytics Maturity Assessment Model (AMAM) serves as the industry standard. Evidence shows that most organizations remain stuck at Stages 0-3, characterized by fragmented data and limited predictive capability (2,29). Healthcare adoption consistently lags behind other sectors like finance (30). Only a small fraction has achieved the advanced governance and AI readiness required for Stages 6-7, a trend reinforced by recent APAC models emphasizing AI governance (31–34).

Maturity directly impacts patient outcomes. Hospitals with advanced digital infrastructure (EMRAM Stage 6-7) demonstrate 3.25 times higher odds of achieving superior safety grades compared to low-maturity peers (35,36). Conversely, low maturity traps organizations in a cycle of reactive decision-making (37,38). While AMAM specifically measures analytics, the correlation between digital maturity and reduced errors is well-established (39,40), though some studies suggest maturity alone is insufficient without workforce stability (41).

Data Quality and Fragmentation: A primary barrier to maturity is systemic data fragmentation. Missing data rates range from 39.7% to 71.0% in cancer registries, while medical registry data shows 2.0-4.6% inaccuracy (8,42,43). Duplicate records affect up to 15% of patient files (44). Automated cleaning tools often fail because they lack the clinical context to resolve ambiguities (45–47). Furthermore, proprietary schemas and poor documentation compel reliance on tacit knowledge (48–50), which is lost during staff transitions (51,52). This creates a “low-maturity trap”: organizations lack the documentation to advance, but lack the stability to create documentation (53–56).

3.2 Pillar 2: Workforce Agility

The healthcare workforce crisis creates an “institutional memory” void. Turnover in healthcare IT exceeds other sectors, with new hires historically averaging just 2.9 years of tenure (1,57). This instability is acute at all levels: 53% of CIOs leave within three years (4), and 55% of public health informatics specialists intend to leave their posts (6). While clinical turnover is well-studied (58,59), technical turnover represents a distinct threat to analytics continuity.

The financial and operational costs are substantial. Replacing a specialist can cost up to $500,000, or three times the annual salary when accounting for lost productivity and recruitment (10,26,60). “Organizational forgetting” occurs when turnover disrupts the collective knowledge structures required for complex tasks (61). In healthcare, this manifests as the loss of “tacit knowledge” - the unwritten business rules and data anomalies that exist only in analysts’ minds (12,62,63).

Traditional knowledge transfer methods fail in this high-turnover environment. Documentation is rarely maintained, and person-to-person transfer breaks down when staff depart faster than replacements can be trained (a process taking 6-18 months) (64–67). This creates a “competence loss” that forces teams to regress to earlier learning stages (10,68). Tacit knowledge is inherently difficult to document and often fails to be captured in formal reports (69,70). The inability to retain expert reasoning leads to “fatal mistakes" in data retrieval, such as normalization errors caused by ambiguous medical terminology (71–75).

3.3 Pillar 3: Technical Enablement

Natural Language to SQL (NL2SQL) generation serves as the technical enabler to bridge the gap between clinical intent and data access. While early models struggled, recent benchmarks show significant progress. GPT-5 and other advanced LLMs now exceed physician baselines on medical reasoning tasks and achieve >80% accuracy on some benchmarks (22,76). However, models remain "not yet sufficiently accurate for unsupervised use" in clinical settings, necessitating human-in-the-loop validation (21,77,78).

Healthcare-specific challenges persist. Medical terminology requires semantic understanding beyond simple keyword matching (68,79). Benchmarks like EHRSQL and MIMICSQL demonstrate that domain-specific architectures significantly outperform general-purpose models (80–85).

Productivity Gains: When implemented effectively, these technologies yield measurable efficiency. Organizations report a 63% increase in self-service analytics adoption and a 37% reduction in data retrieval time (86). Low-code platforms demonstrate similar efficiency gains, accelerating development while abstracting technical complexity (87,88). Clinical query systems reduce formulation time from days to hours, or even seconds (72,89–92). Multimodal interfaces can accelerate query specification by 2.7x to 6.7x compared to typing (93). These gains are driven by code modernization principles that decouple natural language intent from legacy schema complexity, a critical factor in healthcare environments (94–99).

3.4 The Integrated Framework

The framework synthesis reveals that single-pillar interventions fail because the challenges are interdependent.

1. **Maturity ↔ Agility:** Low maturity increases manual workload, driving burnout and turnover. High turnover prevents the accumulation of the "wisdom" (DIKW) needed to advance maturity.
2. **Agility ↔ Enablement:** Without technical enablement, knowledge remains tacit and is lost with turnover. Enablement technologies (Pillar 3) capture this knowledge, decoupling organizational capability from individual tenure (13,100–102).
3. **Enablement ↔ Maturity:** Democratized access (Pillar 3) allows organizations to bypass backend bottlenecks, advancing effective maturity even while infrastructure remains fragmented (103–107).

3.4.1 Illustrative Application: The Validated Query Cycle

To operationalize this framework, we propose the **Validated Query Cycle** (Figure 2), a governance forcing function that addresses institutional memory loss.

1. **Query & Generation:** A domain expert asks a question; the AI generates SQL.
2. **Validation:** The AI explains the logic in natural language. The expert validates the *intent*, creating a "human-on-the-loop" verification (108,109).
3. **Storage & Persistence:** The validated "NL-SQL-Rationale" triple is stored. This distinct software asset captures the business logic (e.g., "Excluding Hospice per 2025 rules") and persists independently of the staff member.
4. **Retrieval:** Future users retrieve this validated knowledge, preventing the need to reinvent complex queries.

This cycle transforms tacit knowledge into an explicit asset, breaking the link between turnover and competency loss.

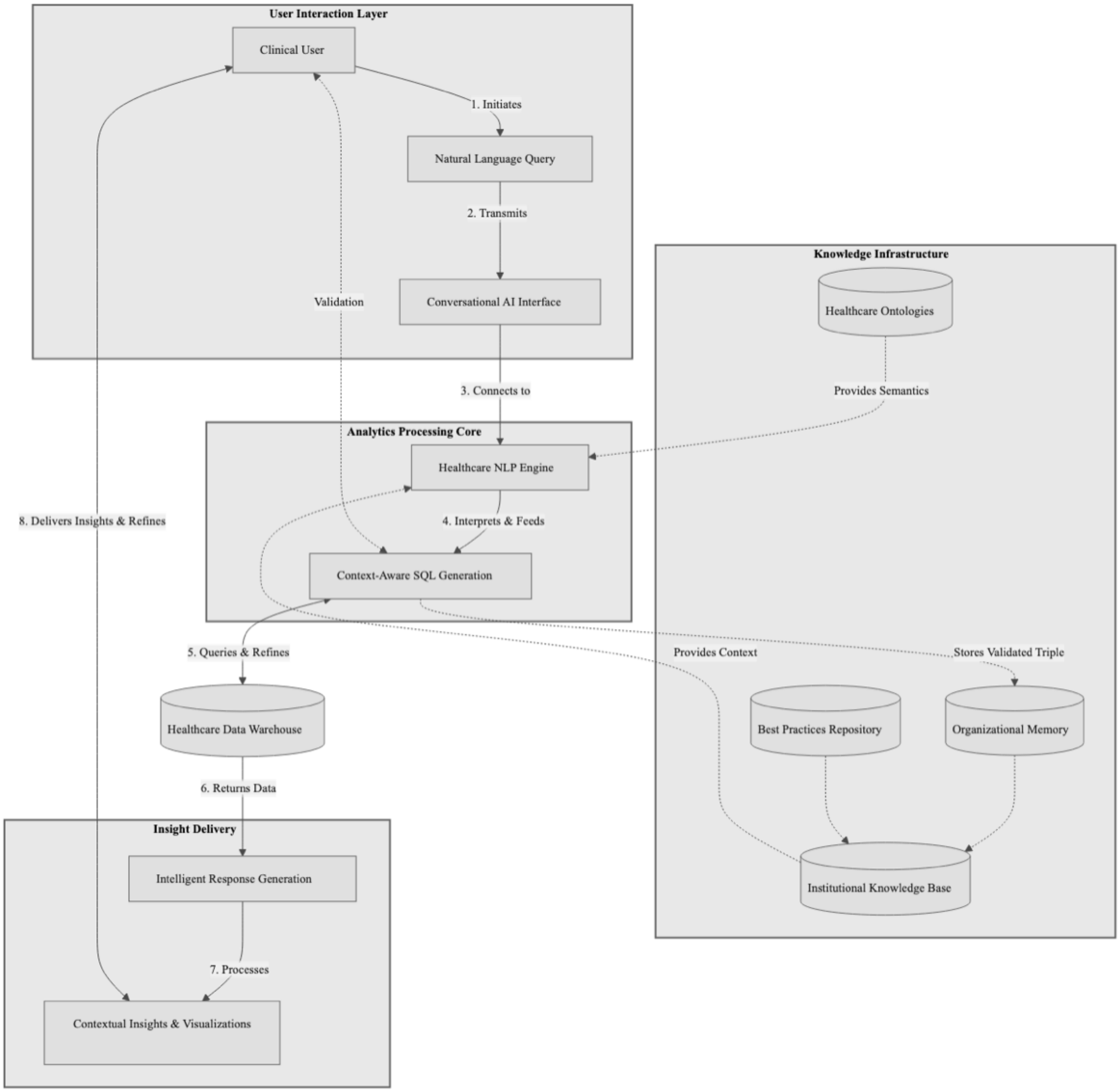

Figure 1: Healthcare Analytics Architecture. Solid lines indicate the primary data flow from clinical user natural language queries through a conversational AI interface to a healthcare NLP engine for context-aware SQL generation. Bi-directional arrows at steps 5 and 8 represent the iterative 'Query & Refine' loop where users refine their intent based on delivered insights. The critical validation step (dotted bi-directional line) shows domain experts confirming or correcting generated SQL before results are trusted. Validated NL-SQL-Rationale triples flow to organizational memory (dashed line), where they persist independent of staff tenure and inform future query generation.

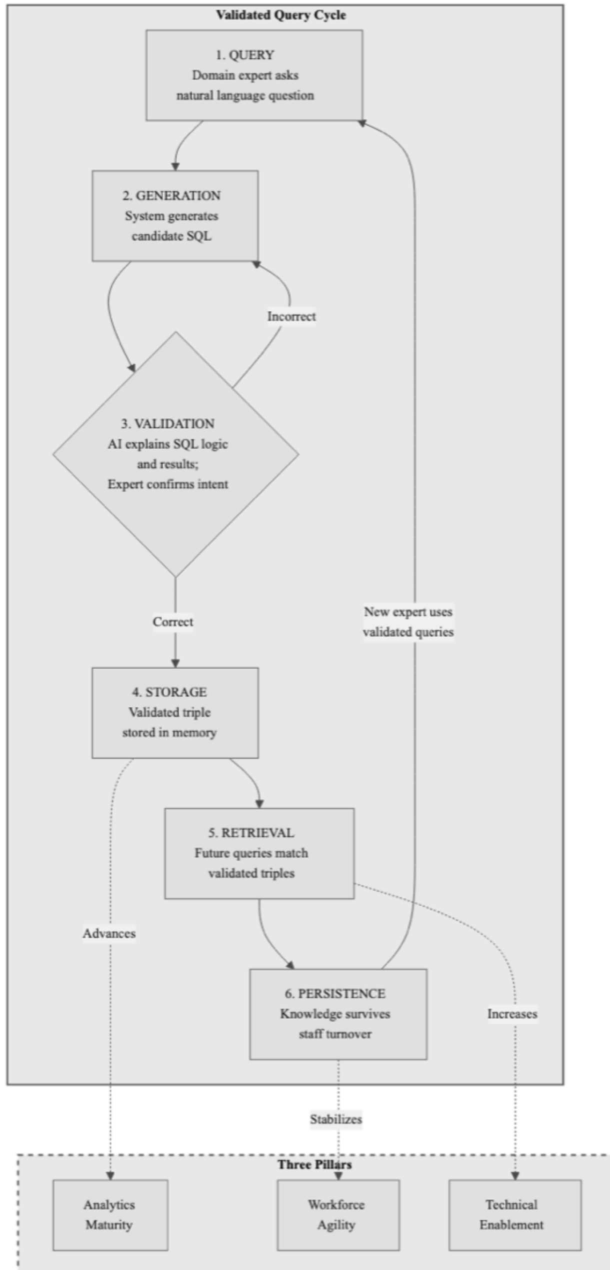

Figure 2: The Validated Query Cycle, shown as six numbered steps in the diagram. (1) Domain experts ask natural language questions, (2) the system generates candidate SQL, (3) AI provides a natural language explanation of the SQL logic; domain expert confirms the intent and results, (4) validated triples are stored, (5) future queries retrieve validated knowledge, and (6) expertise persists through staff turnover. This cycle breaks the compounding effect where turnover erases institutional memory.

4 Discussion

4.1 Market Barriers and Standardization Failure

Efforts to standardize healthcare analytics often fail due to the tension between local clinical reality and centralized models. High-profile industry events illustrate these documented challenges. IBM divested its Watson Health data and analytics assets to Francisco Partners in 2022 (110), following years of underperformance attributed to a fundamental mismatch between AI capabilities and clinical reality: the technology encountered the "messy reality" of healthcare data environments where centralized models failed to account for the highly variable, institution-specific business logic embedded in clinical workflows (111,112). Academic analysis identified additional contributing factors including suboptimal business performance (only breaking even), a restrictive top-down commercialization strategy that limited market reach, and the highly-regulated nature of healthcare creating barriers to AI deployment (112). The Haven healthcare venture (backed by Amazon, Berkshire Hathaway, and JPMorgan Chase) disbanded in 2021 after three years (113), with academic analysis identifying multiple contributing factors: even the three founding companies could not effectively share health-care cost data with each other, the venture never employed more than 75 people (limiting its ability to effect industry-wide change), and leadership turnover destabilized organizational continuity (114). Research on Big Tech platform entry into healthcare positions both Watson Health and Haven within a broader pattern of technology companies encountering regulatory complexity and institutional resistance when attempting to standardize fragmented healthcare systems (115). These outcomes align with the academic literature's findings: standardized solutions face significant barriers when applied across institutions with unique data definitions, business rules, and clinical workflows.

4.2 The Validator Paradox and Knowledge Ratchet

A critical paradox exists: if experts are leaving (Pillar 2), who validates the AI (Pillar 3)? We resolve this via the concept of the "organizational knowledge ratchet" (61). Validation must be reframed not as *eternal truth* but as the "standard work" of informatics, drawing on Lean management principles (116).

In this model, a validated query represents the "current best way" to perform an analysis. As Alukal and Manos (116) establish, standard work is the prerequisite for Kaizen (continuous improvement): without a documented standard, there is no baseline to improve upon. Even provisional validation by mid-level analysts captures operational logic into a durable artifact. This prevents the "sliding back to zero" characteristic of high-turnover environments (75). Rather than requiring a permanent core of experts, the system accumulates knowledge incrementally, using the structure of the validation process to buffer against the disruptive effects of turnover.

4.3 Lifecycle Management: Continuous Analytic Integration

Leveraging the property of Executability, a validated SQL query is treated not as a static artifact but as a software asset within a CI/CD pipeline. In healthcare, database schemas (Epic, Cerner, OMOP) change frequently, breaking “frozen” code. To address “Schema Drift,” analytics must adopt principles from software engineering: *Continuous Analytic Integration*. In this approach, Validated Query Triples are managed not as wiki entries but as software assets within a CI/CD pipeline. When the data warehouse schema is updated (e.g., a quarterly EHR upgrade), the system automatically re-runs the library of stored queries. Queries that fail or return anomalous results are flagged for review. This transforms “Institutional Memory” from a stagnant repository into a living, automated test suite that actively signals when organizational knowledge has drifted from technical reality.

4.4 Mitigating “Shadow IT” with “Golden Queries”

To prevent the “chaos of conflicting definitions” that can arise from democratized analytics, organizations can introduce a “Golden Query” governance status. In this model, a central committee can certify specific validated triples as the “source of truth” for the organization (117). This ensures that while many users can create and validate queries, only a select few are designated as the official, trusted queries for key metrics, thus mitigating the risks of “Shadow IT” (118).

4.5 Economic and Strategic Implications

The economic case for intervention is supported by evidence linking conversational analytics to a 206% three-year ROI and reduced development times (28,119–122). Low-code and AI platforms democratize access, allowing organizations to achieve “Shadow IT” agility within a governed framework (117,118,123,124). Other benefits include faster revenue cycles (125) and cost reductions (126–129).

4.6 Limitations and Future Research

This review is limited by its narrative design and the rapid evolution of the field. Evidence gaps remain regarding long-term outcomes (130), specialty-specific applications, and governance frameworks for democratized analytics. Future research should prioritize: (1) validation of NL2SQL on synthetic healthcare data (e.g., Synthea), (2) automated schema discovery algorithms, and (3) longitudinal studies of organizational transformation.

5 Conclusion

We developed a three-pillar analytical framework connecting analytics maturity, workforce agility, and technical enablement. The evidence reveals that these challenges are self-reinforcing: low maturity accelerates turnover, turnover degrades the institutional memory needed for maturity, and technical barriers prevent knowledge capture.

By deploying technical enablement - specifically conversational AI with a validated query cycle - organizations can break this cycle. This approach captures tacit knowledge as executable artifacts, ensuring that expertise persists independently of individual staff tenure. Applying the principle of *primum non nocere*, healthcare leaders must recognize that inaction in the face of workforce instability allows the continued degradation of organizational capability.

6 Acknowledgments

The author (S.T.H.) takes full responsibility for the final content. Gemini CLI (Gemini 3, Google) assisted with manuscript editing and refinement. The author takes full responsibility for the final content.

7 Funding

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

8 Abbreviations

AACODS: Authority, Accuracy, Coverage, Objectivity, Date, Significance AI: Artificial Intelligence AMAM: Analytics Maturity Assessment Model CIO: Chief Information Officer DIKW: Data-Information-Knowledge-Wisdom EHR: Electronic Health Record EMRAM: Electronic Medical Record Adoption Model HIMSS: Healthcare Information Management Systems Society IT: Information Technology NL2SQL: Natural Language to SQL NLP: Natural Language Processing SQL: Structured Query Language

9 Author Contributions

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

10 Conflicts of Interest

The author is a contract product advisor at Yuimedi, Inc. and employed at Indiana University Health. The views expressed are the author's own.

11 Data Availability

This is a narrative review; no primary datasets were generated.

12 References

1. 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/

2. 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/

3. 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

4. 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

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

6. 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

7. 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/

8. 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.

9. Rowley J. The wisdom hierarchy: representations of the DIKW hierarchy. Journal of Information Science. 2007;33(2):163–80.

10. 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

11. 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

12. 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

13. 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

14. 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

15. Allison DG, Peters H. Root Cause Analysis (RCA) for the Improvement of Healthcare Systems and Patient Safety [Internet]. CRC Press; 2021. Available from: https://doi.org/10.1201/9781003188162

16. Soylemez M, Tarhan A. A Review and Comparison of Maturity/Capability Frameworks for Healthcare Process Assessment and Improvement. Software Quality Professional [Internet]. 2017;19:28–42. Available from: https://openurl.ebsco.com/EPDB%3Agcd%3A3%3A34056963/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A121526814

17. Latrella &B M. Improving patient outcomes while reducing readmissions with data analytics. Management in Healthcare [Internet]. 2024; Available from: https://www.ingentaconnect.com/content/hsp/mih/2024/00000008/00000004/art00006

18. Nashid P S., Hossain MI. Advanced Business Analytics in Healthcare: Enhancing Clinical Decision Support and Operational Efficiency. Business and Social Sciences [Internet]. 2023;1(1):1–8. Available from: https://doi.org/10.25163/business.1110345

19. Shahbaz G M. Investigating the adoption of big data analytics in healthcare: The moderating role of resistance to change. Journal of Big Data [Internet]. 2019; Available from: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0170-y

20. Kamble G S. S. A systematic perspective on the applications of big data analytics in healthcare management. International Journal of Healthcare Management [Internet]. 2019; Available from: https://www.tandfonline.com/doi/full/10.1080/20479700.2018.1531606

21. 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

22. Wang H S. Capabilities of GPT-5 on multimodal medical reasoning. arXiv preprint [Internet]. 2025; Available from: https://arxiv.org/abs/2508.08224

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

24. Trust BHN. Empowering citizen developers: Low-code success in healthcare [Internet]. 2024. Available from: https://ia.berkshirehealthcare.nhs.uk/citizen-developer-programme

25. Snowdon A. New analytics maturity adoption model pushes for digital transformation and data-driven decisions. HIMSS [Internet]. 2024; Available from: https://legacy.himss.org/news/new-analytics-maturity-adoption-model-pushes-digital-transformation-and-data-driven-decisions

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

27. 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

28. Research F. The total economic impact of Microsoft Power Apps. Forrester Consulting [Internet]. 2024. Available from: https://tei.forrester.com/go/microsoft/powerappstei/?lang=en-us

29. 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

30. Wang &H Y. Exploring the path to big data analytics success in healthcare. Journal of Business Research [Internet]. 2017; Available from: https://www.sciencedirect.com/science/article/abs/pii/S0148296316304891

31. Tampa General Hospital. Tampa General Hospital Awarded Highest Designation in Analytics by HIMSS [Internet]. 2025. Available from: https://www.tgh.org/news/tgh-press-releases/2025/june/tampa-general-hospital-awarded-highest-designation-analytics-himss

32. China Medical University Hospital. Taiwan's First Hospital to Achieve AMAM Stage 7 Certification! [Internet]. PR Newswire; 2025. Available from: https://www.prnewswire.com/news-releases/taiwans-first-hospital-to-achieve-amam-stage-7-certification-302390824.html

33. Medical Buyer. 2 medical groups in Saudi Arabia achieve stage 7 digital maturity [Internet]. 2024. Available from: https://medicalbuyer.co.in/2-medical-groups-in-saudi-arabia-achieve-stage-7-digital-maturity/

34. Healthcare IT News. At HIMSS24 APAC, the Adoption Model for Analytics Maturity gets facelift [Internet]. 2024. Available from: https://www.healthcareitnews.com/news/asia/himss24-apac-adoption-model-analytics-maturity-gets-facelift

35. 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

36. Snowdon H A. Digital maturity as a strategy for advancing patient experience in US hospitals. Journal of Patient Experience [Internet]. 2024; Available from: https://journals.sagepub.com/doi/full/10.1177/23743735241253785

37. Wang K Y. Leveraging big data analytics to improve quality of care in healthcare organizations: A configurational perspective. British Journal of Management [Internet]. 2019; Available from: https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8551.12332

38. Gomes &R J. Evaluating maturity models in healthcare information systems: A comprehensive review. Healthcare [Internet]. 2025; Available from: https://www.mdpi.com/2227-9032/13/1/1

39. Woods L, Eden R, Green D, Pearce A. Impact of digital health on the quadruple aims of healthcare: A correlational and longitudinal study (Digimat Study). International Journal of Medical Informatics [Internet]. 2024; Available from: https://www.sciencedirect.com/science/article/pii/S1386505624001916

40. Martin G, Clarke J, Liew F, Arora S, King D, Aylin P. Evaluating the impact of organisational digital maturity on clinical outcomes in secondary care in England. npj Digital Medicine [Internet]. 2019; Available from: https://www.nature.com/articles/s41746-019-0118-9

41. Saint-Ulysse C. The Relationship between Hospitals' Electronic Health Records Maturity and Excess Readmission Ratio [Internet]. Walden University Dissertations; 2021. Available from: https://scholarworks.waldenu.edu/cgi/viewcontent.cgi?article=12395&context=dissertations

42. 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

43. Arts DG, De Keizer NF, et al. Defining and improving data quality in medical registries: a literature review, case study, and generic framework. Journal of the American Medical Informatics Association [Internet]. 2002;9(6):600–11. Available from: https://academic.oup.com/jamia/article-abstract/9/6/600/1036696

44. McCoy AB, Wright A, Kahn MG, Shapiro JS, et al. Matching identifiers in electronic health records: implications for duplicate records and patient safety. BMJ Quality & Safety [Internet]. 2013;22(3):219–24. Available from: https://qualitysafety.bmj.com/content/22/3/219.short

45. Rahman P, Nandi A, Hebert C. Amplifying domain expertise in clinical data pipelines. JMIR Medical Informatics [Internet]. 2020;8(11):e19612. Available from: https://medinform.jmir.org/2020/11/e19612/

46. Sirgo G, Esteban G Francisco icon, Moreno G, et al. Validation of the ICU-DaMa tool for automatically extracting variables for minimum dataset and quality indicators: The importance of data quality assessment. International Journal of Medical Informatics [Internet]. 2018;112:166–72. Available from: https://www.sciencedirect.com/science/article/abs/pii/S1386505618300443

47. Shi X, Prins C, Van Pottelbergh G, Mamouris P, et al. An automated data cleaning method for Electronic Health Records by incorporating clinical knowledge. BMC Medical Informatics and Decision Making [Internet]. 2021;21:1–12. Available from: https://link.springer.com/article/10.1186/s12911-021-01470-5

48. Dugas M, Neuhaus P, Meidt A, Doods J, Storck M, et al. Portal of medical data models: information infrastructure for medical research and healthcare. Database [Internet]. 2016;2016. Available from: https://academic.oup.com/database/article/doi/10.1093/database/bav121/2630096

49. Bokov AF, Bos AB, Manuel LS, et al. Using prevalence patterns to discover un-mapped flowsheet data in an electronic health record data warehouse. In: 2017 IEEE 30th international symposium on computer-based medical systems (CBMS) [Internet]. IEEE; 2017. p. 509–14. Available from: https://ieeexplore.ieee.org/abstract/document/8104211

50. Ulrich H, Kock-Schoppenhauer AK, et al. Understanding the nature of metadata: systematic review. Journal of Medical Internet Research [Internet]. 2022;24(1):e25440. Available from: https://www.jmir.org/2022/1/e25440/

51. Lucyk K, Tang K, Quan H. Barriers to data quality resulting from the process of coding health information to administrative data: a qualitative study. BMC Health Services Research [Internet]. 2017;17(1):1–10. Available from: https://link.springer.com/article/10.1186/s12913-017-2697-y

52. Hovenga EJ, Grain H. Health data and data governance. In: Health information governance in a digital environment [Internet]. IOS Press; 2013. p. 67–94. Available from: https://ebooks.iospress.nl/volumearticle/35106

53. Carvalho JV, Rocha Á, Vasconcelos J. A health data analytics maturity model for hospitals information systems. International Journal of Information Management. 2019;46:278–85.

54. Pinto-Valverde J, Pérez-Guardado M. HDQM2: healthcare data quality maturity model. In: Midwest association for information systems conference [Internet]. 2013. Available from: https://scholarworks.wmich.edu/ichita_transactions/37/

55. G”okalp MO, G”okalp E, G”okalp S. The development of data analytics maturity assessment framework: DAMAF. Journal of Software: Evolution and Process [Internet]. 2023;35(4):e2448. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/smr.2415

56. Lismont J, Vanthienen J, Baesens B, et al. Defining analytics maturity indicators: A survey approach. International Journal of Information Management [Internet]. 2017;37(3):114–24. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0268401216305655

57. 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

58. 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/

59. 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/

60. Willard-Grace K R. Burnout and health care workforce turnover. The Annals of Family Medicine [Internet]. 2019; Available from: https://www.annfammed.org/content/17/1/36

61. 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

62. 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

63. 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

64. 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

65. 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/

66. Musa D S. The impact of training on electronic health records related knowledge, practical competencies, and staff satisfaction: A pre-post intervention study among wellness center providers in a primary health-care facility. Journal of Multidisciplinary Healthcare [Internet]. 2023; Available from: https://pmc.ncbi.nlm.nih.gov/articles/PMC10243608/

67. 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

68. 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

69. Goffin K K. Managing lessons learned and tacit knowledge in new product development. Research-Technology Management [Internet]. 2010; Available from: https://www.tandfonline.com/doi/abs/10.1080/08956308.2010.11657637

70. Rintala &H N. Methods for sharing tacit nuclear knowledge and expertise. International Journal of Nuclear Knowledge Management [Internet]. 2006; Available from: https://www.inderscienceonline.com/doi/abs/10.1504/IJNKM.2006.009880

71. Bardsley M. Understanding analytical capability in health care: Do we have more data than insight? The Health Foundation [Internet]. 2016. Available from: https://www.health.org.uk/publications/understanding-analytical-capability-in-health-care

72. Yuan R C. Criteria2Query: a natural language interface to clinical databases for cohort definition. Journal of the American Medical Informatics Association [Internet]. 2019; Available from: https://academic.oup.com/jamia/article-abstract/26/4/294/5308980

73. Pesqueira S A. Big data skills sustainable development in healthcare and pharmaceuticals. Journal of Medical Systems [Internet]. 2020; Available from: https://link.springer.com/article/10.1007/s10916-020-01665-9

74. 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

75. 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

76. OpenAI. HealthBench: A benchmark for evaluating LLMs in healthcare. arXiv preprint [Internet]. 2025; Available from: https://arxiv.org/abs/2505.08775

77. Wu Q C., Xie W. Towards evaluating and building versatile large language models for medicine. npj Digital Medicine [Internet]. 2025; Available from: https://www.nature.com/articles/s41746-024-01390-4

78. Jiang B Y., Chen JH. MedAgentBench: A virtual EHR environment to benchmark medical LLM agents. NEJM AI [Internet]. 2025; Available from: https://ai.nejm.org/doi/full/10.1056/AIdbp2500144

79. Navarro I D. F. Clinical named entity recognition and relation extraction using natural language processing of medical free text: A systematic review. International Journal of Medical Informatics [Internet]. 2023; Available from: https://www.sciencedirect.com/science/article/pii/S1386505623001405

80. 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

81. Sivasubramaniam OA S. SM3-Text-to-Query: Synthetic multi-model medical text-to-query benchmark. Advances in Neural Information Processing Systems [Internet]. 2024; Available from: https://arxiv.org/abs/2411.05521

82. Lee C G. SCARE: A benchmark for SQL correction and question answerability classification for reliable EHR question answering. arXiv preprint [Internet]. 2025; Available from: https://arxiv.org/abs/2511.17559

83. Chen P Q. Graph-empowered text-to-SQL generation on electronic medical records. Pattern Recognition [Internet]. 2025; Available from: https://www.sciencedirect.com/science/article/pii/S0031320324008197

84. Blašković T L., Lorencin I. Robust clinical querying with local LLMs: Lexical challenges in NL2SQL and RAG-QA on EHRs. Big Data and Cognitive Computing [Internet]. 2025;9(10):256. Available from: https://www.mdpi.com/2504-2289/9/10/256

85. 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

86. 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

87. Atobatele A O. K. Transforming digital health information systems with Microsoft Dynamics, SharePoint, and low-code automation platforms. Gyanshauryam International Scientific Refereed Research Journal [Internet]. 2023; Available from: https://gisrrj.com/paper/GISRRJ236426.pdf

88. Aveiro F D. Traditional vs. low-code development: comparing needed effort and system complexity in the NexusBRaNT experiment. In: 2023 IEEE 25th conference on business informatics (CBI) [Internet]. 2023. Available from: https://ieeexplore.ieee.org/document/10186753

89. Park F J. Criteria2Query 3.0: Leveraging generative large language models for clinical trial eligibility query generation. Journal of Biomedical Informatics [Internet]. 2024; Available from: https://www.sciencedirect.com/science/article/pii/S1532046424000650

90. 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

91. Safari &P L. Restricted natural language based querying of clinical databases. Journal of Biomedical Informatics [Internet]. 2014; Available from: https://www.sciencedirect.com/science/article/pii/S1532046414001592

92. Han C J. Improving the efficacy of the data entry process for clinical research with a natural language processing-driven medical information extraction system. JMIR Medical Informatics [Internet]. 2019; Available from: https://medinform.jmir.org/2019/3/e13331

93. Shah L V. SpeakQL: towards speech-driven multimodal querying of structured data. In: Proceedings of the 2020 ACM SIGMOD international conference on management of data [Internet]. 2020. Available from: https://dl.acm.org/doi/abs/10.1145/3318464.3389777

94. Hendrix S G. G. Developing a natural language interface to complex data. ACM Transactions on Database Systems [Internet]. 1978; Available from: https://dl.acm.org/doi/abs/10.1145/320251.320253

95. Saha G B. K. NLINQ: A natural language interface for querying network performance. International Journal of Network Management [Internet]. 2023;33(4):e2225. Available from: https://www.proquest.com/openview/0d955ee8209664a4447c9995a1b9e721/1?pq-origsite=gscholar&cbl=326365

96. Khandelwal AP. AI-Driven Mainframe Modernization: Unlocking Legacy Data for Cloud Analytics. Journal of Engineering and Computer Sciences [Internet]. 2025; Available from: https://sarcouncil.com/2025/06/ai-driven-mainframe-modernization-unlocking-legacy-data-for-cloud-analytics

97. Ogunwole &O O. Modernizing legacy systems: A scalable approach to next-generation data architectures and seamless integration. International Journal of Multidisciplinary Research [Internet]. 2023; Available from: https://www.allmultidisciplinaryjournal.com/uploads/archives/20250306182550_MGE-2025-2-018.1.pdf

98. Arora A. Challenges of Integrating Artificial Intelligence in Legacy Systems and Potential Solutions for Seamless Integration. SSRN [Internet]. 2025; Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5268176

99. Anthropic. Code modernization playbook: A practical guide to modernizing legacy systems with AI [Internet]. 2025. Available from: https://resources.anthropic.com/code-modernization-playbook

100. 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

101. Rangachari &W P. Preserving organizational resilience, patient safety, and staff retention during COVID-19 requires a holistic consideration of the psychological safety of healthcare workers. International Journal of Environmental Research and Public Health [Internet]. 2020; Available from: https://www.mdpi.com/1660-4601/17/12/4267

102. 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

103. Syed S, Nampalli RCR, Vankayalapati RK, Yasmeen Z. Advancing Self-Service BI: The Rise of Autonomous Analytics Powered by Machine Learning [Internet]. Syed Publication; 2025. Available from: https://www.google.com/books/edition/ADVANCING_SELFSERVICE_BI_The_Rise_of_Aut/np01EQAAQBAJ

104. Samimi R, Bhattacharya A, Gosak L, Stiglic G, Verbert K. Visual-Conversational Interface for Evidence-Based Explanation of Diabetes Risk Prediction. In: Proceedings of the 7th ACM conference on conversational user interfaces. 2025.

105. Ruoff M, Gnewuch U, Maedche A, Scheibehenne B. Designing Conversational Dashboards for Effective Use in Crisis Response. Journal of the Association for Information Systems. 2023;24(6):1500–26.

106. Chowdhury I, Moeid A, Hoque E, Kabir MA. Designing and evaluating multimodal interactions for facilitating visual analysis with dashboards. IEEE Access [Internet]. 2020; Available from: https://ieeexplore.ieee.org/abstract/document/9303381

107. Holmes S, Moorhead A, Bond R, Zheng H. Usability testing of a healthcare chatbot: Can we use conventional methods to assess conversational user interfaces? In: Proceedings of the 31st european conference on cognitive ergonomics [Internet]. 2019. Available from: https://dl.acm.org/doi/abs/10.1145/3335082.3335094

108. 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

109. 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

110. 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

111. 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/

112. 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

113. 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

114. 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

115. Ozalp H, Ozcan P, Dinckol D. "Digital colonization" of highly regulated industries: an analysis of big tech platforms' entry into health care. California Management Review [Internet]. 2022;64(4):78–107. Available from: https://journals.sagepub.com/doi/abs/10.1177/00081256221094307

116. 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

117. 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

118. Zimmermann S, Rentrop C, Felden C. A Multiple Case Study on the Nature and Management of Shadow Information Technology. Journal of Information Systems. 2017;31(1):79–101.

119. El Kamouchi &K H. Low-code/No-code Development: A systematic literature review. In: 2023 14th international conference on computing communication and networking technologies (ICCCNT) [Internet]. 2023. Available from: https://ieeexplore.ieee.org/abstract/document/10373712/

120. Mogili VB. Healthcare and Finance Transformation through Enterprise Content, Low-Code, and Automation: A Multinational Technology Corporation's Approach. Journal of Engineering and Computer Sciences [Internet]. 2025; Available from: https://sarcouncil.com/download-article/SJECS-209-_2025-630-636.pdf

121. Pervaiz &I H. Leveraging Low-Code/No-Code Platforms for Rapid Digital Transformation in Small and Medium-sized Enterprises (SMEs). Multidisciplinary Journal of Science, Technology & Business [Internet]. 2025; Available from: https://imjstb.com/index.php/Journal/article/view/95

122. Research P. Healthcare analytics market size and forecast 2025 to 2034 [Internet]. 2024. Available from: https://www.precedenceresearch.com/healthcare-analytics-market

123. Rivard S. Successful Implementation of End-User Computing. Interfaces. 1987;17(3):25–33.

124. Kopper A, Westner M, Strahringer S. From Shadow IT to Business-managed IT: a qualitative comparative analysis to determine configurations for successful management of IT by business entities. Information Systems and e-Business Management. 2020;18:209–57.

125. Pennington R. Artificial intelligence (AI) and its opportunity in healthcare organizations revenue cycle management (RCM) [Internet] [Master's thesis]. 2023. Available from: https://mds.marshall.edu/etd/1824/

126. Jiao Z W. The economic value and clinical impact of artificial intelligence in healthcare: A scoping literature review. IEEE Access [Internet]. 2023; Available from: https://ieeexplore.ieee.org/document/10297311

127. 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

128. Nashid S, Papia SK, Chowdhury N, Mia MS, Hossain MI. Advanced Business Analytics in Healthcare Enhancing Clinical Decision Support and Operational Efficiency. Business and Social Sciences [Internet]. 2023;1(1):1–8. Available from: https://doi.org/10.25163/business.1110345

129. Forrester Consulting. The Total Economic Impact™ Of Microsoft Power Apps [Internet]. Forrester Consulting; 2024. Available from: https://tools.totaleconomicimpact.com/go/microsoft/powerapps/

130. Sezgin S E. Operationalizing and implementing pretrained, large artificial intelligence linguistic models in the US health care system: Outlook of generative pretrained transformer 3 (GPT-3) as a service model. JMIR Medical Informatics [Internet]. 2022; Available from: https://medinform.jmir.org/2022/2/e32875