
Healthcare Analytics Challenges: A Three-Pillar Framework Connecting Analytics Maturity, Workforce Dynamics, and Technical Barriers

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Background: Healthcare organizations face three interconnected challenges that form a compounding cycle: low analytics maturity (only 39 organizations globally have achieved HIMSS AMAM Stage 6-7), high workforce turnover (34% annually for healthcare IT staff as of 2004), 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 healthcare analytics maturity gaps, workforce turnover, and technical barriers to data access. The framework reveals how these challenges interconnect and compound each other.

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

Results: Healthcare-specific text-to-SQL benchmarks (EHRSQL, SM3-Text-to-Query) 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 three-pillar framework reveals compounding dynamics: organizations at low maturity stages experience higher turnover, turnover degrades institutional knowledge needed for maturity advancement, and technical barriers prevent capturing expertise before it is lost.

Conclusions: We contribute a three-pillar analytical framework synthesizing evidence on healthcare analytics maturity, workforce dynamics, and technical barriers. The framework reveals compounding effects: low maturity accelerates turnover, turnover degrades maturity, and technical barriers prevent recovery. This analytical lens enables organizational self-assessment and informs future research on technology interventions, including conversational AI platforms as one potential application.

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1 Introduction

1.1 Background

Healthcare analytics has emerged as a critical capability for improving patient outcomes, reducing costs, and enhancing operational efficiency. While healthcare organizations must balance cost management, regulatory compliance, and operational efficiency, these concerns serve a primary institutional imperative: delivering high-quality patient care. Analytics initiatives that fail to advance this core mission, or worse, that divert resources and attention without improving care delivery, represent a misalignment with healthcare’s fundamental purpose.

However, the sector faces unique challenges that distinguish it from other data-intensive industries. 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).

The Healthcare Information Management Systems Society (HIMSS) Analytics Maturity Assessment Model (AMAM) provides the industry standard for measuring healthcare analytics capabilities across seven stages, from basic data collection to advanced predictive modeling and AI integration. Recent assessments reveal a sobering reality: as of 2024, only 26 organizations worldwide have achieved Stage 6 maturity, with merely 13 reaching Stage 7, the highest level characterized by predictive analytics and AI integration (2).

This analytics maturity crisis occurs amid accelerating technological advances in natural language processing and conversational AI. Large language models have demonstrated remarkable capabilities in understanding clinical terminology, generating SQL queries, and bridging the gap between natural language questions and structured data analysis. These developments create unprecedented opportunities to democratize healthcare analytics access.

Simultaneously, healthcare faces an institutional memory crisis driven by workforce turnover rates significantly higher than other knowledge-intensive sectors. A 2004 study found healthcare IT staff turnover of 34% (3), the highest rate among all IT organization types studied at that time, creating cascading knowledge loss, particularly in analytics roles where expertise combines domain knowledge with technical skills. Traditional knowledge management approaches prove inadequate for preserving the tacit knowledge essential for effective healthcare data analysis.

1.2 Problem Statement

Healthcare organizations face three critical, interconnected challenges that collectively threaten their ability to become data-driven enterprises:

1.2.1 Low Healthcare Analytics Maturity

Despite massive investments in electronic health records and data infrastructure, healthcare organizations struggle to advance beyond basic reporting capabilities. The HIMSS AMAM reveals that most organizations remain at Stages 0-3, characterized by fragmented data sources, limited automated reporting, and minimal predictive capabilities (2). This low maturity severely constrains evidence-based decision making and operational optimization.

1.2.2 Technical Barriers to Data Access

Healthcare professionals possess deep clinical knowledge but lack the technical skills required for data analysis. Traditional analytics tools require SQL expertise, statistical knowledge, and familiarity with complex database schemas, capabilities that clinical staff often do not possess nor have time to develop. This creates a fundamental disconnect between those who understand the clinical questions and those who can access the data to answer them (4), (5), (6). Drawing on principles from code modernization, AI-assisted interfaces can bridge this gap by transforming legacy technical requirements into natural language interactions (7). Foundational research on natural language interfaces to databases established that modular architecture principles enable effective bridging of legacy data access challenges (8), with modern implementations demonstrating that the same large language models underlying code modernization can serve as natural language interfaces to legacy systems (9), (10).

1.2.3 Institutional Memory Loss from Workforce Turnover

A 2004 study found healthcare IT staff experienced the highest turnover among IT sectors at 34% annually (calculated as 1/2.9 years average tenure), with average tenure of only 2.9 years, the lowest among IT sectors studied at that time (3). This creates significant institutional memory loss. When experienced analysts, clinical informatics professionals, or data-savvy clinicians leave, they take with them irreplaceable knowledge about data definitions, business rules, analytical approaches, and organizational context. This knowledge proves extremely difficult to document and transfer through traditional means.

The implications are measurable in operational terms and patient care quality. Organizations continue investing in analytics infrastructure while struggling to realize value from their data assets. Empirical research demonstrates that a 10-percentage-point increase in nursing staff turnover is associated with 0.241 additional health inspection citations and decreased assessment-based quality measures (11). When analytics barriers are addressed, outcomes improve substantially: one Medicare ACO reduced readmission rates from 24% to 17.8% and achieved \$1.6 million in cost savings by implementing data analytics to overcome EHR fragmentation (12). Technical barriers remain pervasive, with 68% of healthcare organizations citing data interoperability as the leading obstacle to analytics adoption, followed by privacy concerns (64%) and insufficient staff training (59%) (13). Physician technology adoption faces empirically validated barriers including perceived threat and inequity from workflow changes, directly impacting behavioral intentions toward analytics tools (14). These three interconnected challenges represent operational inefficiencies with demonstrated implications for healthcare delivery.

1.3 Objectives

This research aims to develop and validate an analytical framework for understanding healthcare’s interconnected analytics challenges. Specific objectives include:

1.3.1 Primary Objective

Develop and validate a three-pillar analytical framework for understanding how healthcare analytics maturity gaps, workforce turnover, and technical barriers interconnect and compound each other.

1.3.2 Secondary Objectives

1. **Synthesize current evidence** on natural language to SQL generation as one dimension of technical barriers
2. **Document the extent** of analytics maturity challenges across healthcare organizations globally
3. **Quantify the impact** of workforce turnover on institutional memory and analytics capabilities
4. **Reveal interconnections** between the three pillars through evidence synthesis
5. **Provide assessment rubric** for organizational self-evaluation using the framework

1.3.3 Non-Goals

This research explicitly does not address:

- Specific vendor comparisons or product recommendations
- Implementation details for particular healthcare IT environments
- Regulatory compliance strategies for specific jurisdictions
- Technical architecture specifications for conversational AI systems

Note: Analysis of market dynamics and structural factors explaining why institution-specific analytics challenges persist is within scope. This market-level analysis provides necessary context for evaluating solution approaches and differs from product comparison, which would evaluate specific vendor offerings against each other or recommend particular products.

1.4 Contributions

This paper makes the following contributions to the healthcare informatics literature:

1. **Three-Pillar Analytical Framework** (Primary Contribution): We synthesize evidence from three previously disconnected research domains (healthcare analytics maturity, workforce turnover, and natural language processing) into a unified analytical framework that reveals how these challenges interconnect and compound each other: low maturity accelerates turnover, turnover degrades maturity, and technical barriers prevent recovery from either. This framework provides an analytical lens for organizational self-assessment and research prioritization.
2. **Evidence Synthesis Across Domains**: We document the current state of each pillar through comprehensive literature review, providing healthcare organizations with consolidated evidence on analytics maturity benchmarks, workforce turnover impacts, and NL2SQL technical capabilities.
3. **Illustrative Application**: Drawing on established knowledge management literature (15,16), we describe the validated query cycle as one example of how the framework might inform technology design. This architecture concept addresses institutional memory loss through six steps: (1) domain experts ask natural language questions, (2) the system generates candidate SQL, (3) experts validate and correct the SQL, (4) validated NL+SQL pairs are stored in organizational memory, (5) future queries retrieve validated pairs, and (6) knowledge persists independent of staff tenure. Figure 1 illustrates this architecture, and Figure 2 details the validated query cycle.

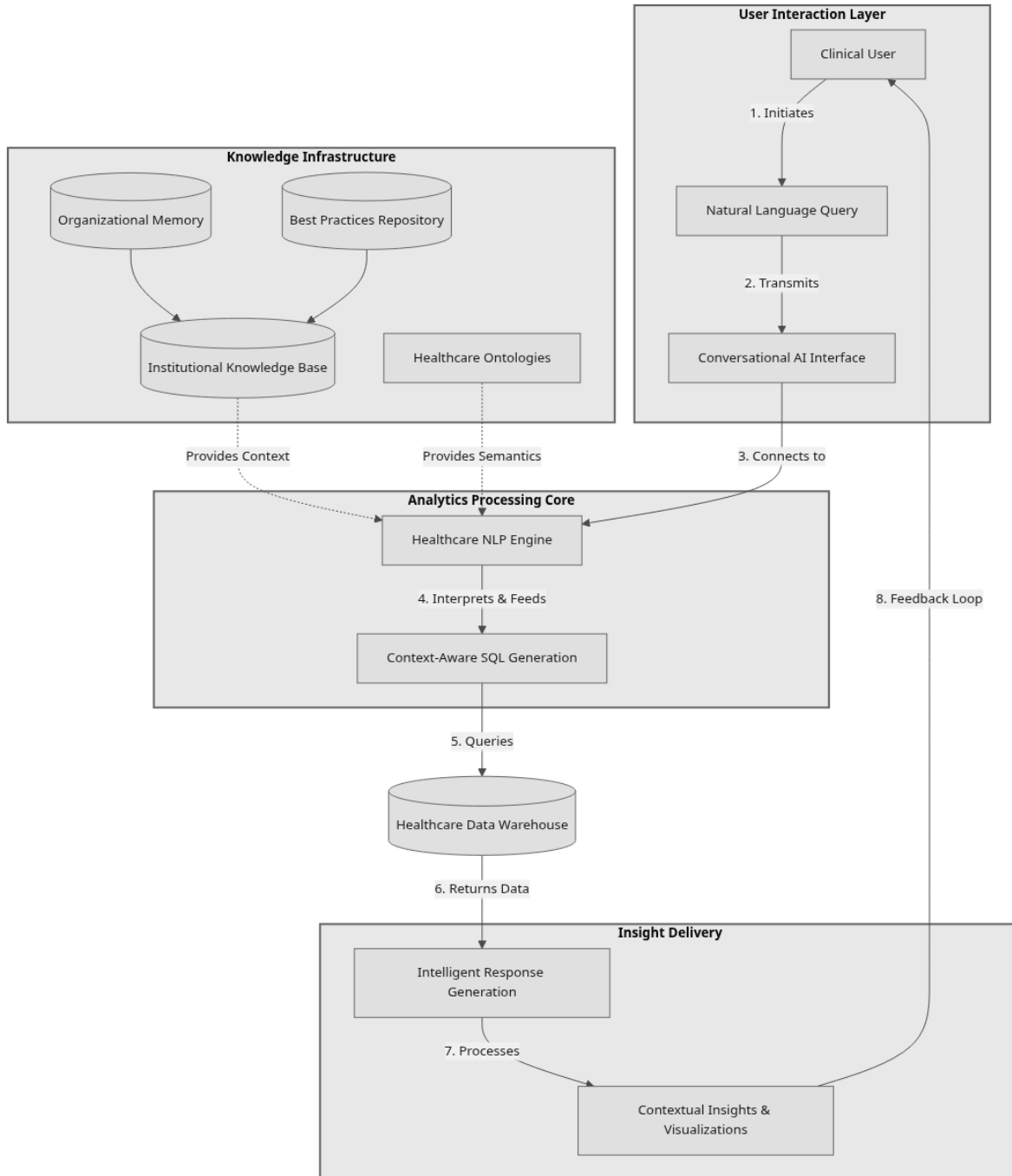


Figure 1: Healthcare Analytics Architecture. Solid lines indicate the primary data flow from clinical user natural language queries through a conversational AI interface to a healthcare NLP engine for context-aware SQL generation against a healthcare data warehouse, ultimately delivering contextual insights. The critical validation step (dotted line) shows domain experts confirming or correcting generated SQL before results are trusted. Validated NL+SQL pairs flow to organizational memory (dashed line), where they persist independent of staff tenure and inform future query generation.

1.4.1 Illustrative Application: The Validated Query Cycle

To demonstrate how the three-pillar framework might inform technology design, we describe a validated query cycle that could address institutional memory loss (Pillar 2) while reducing technical barriers (Pillar 3). This six-step cycle (Figure 2) illustrates one approach:

1. **Query:** A domain expert (clinician, analyst, or administrator) asks a natural language question about organizational data, such as “What was our 30-day readmission rate for heart failure patients last quarter?”
2. **Generation:** The conversational AI system generates candidate SQL code from the natural language input, leveraging healthcare ontologies and organizational schema knowledge to produce syntactically correct queries.
3. **Validation:** The domain expert reviews the generated SQL and its results, confirming correctness or providing corrections. This human-in-the-loop step is essential because current NL2SQL models are “not yet sufficiently accurate for unsupervised use” in clinical settings (17).
4. **Storage:** Once validated, the NL+SQL pair is stored in organizational memory as a durable knowledge artifact. This pair represents tested, executable knowledge: a verified mapping from a business question to the correct data retrieval logic.
5. **Retrieval:** When future users ask similar questions, the system retrieves relevant validated pairs, either returning exact matches or using them to inform new query generation. This reduces dependence on individual expertise.
6. **Persistence:** When the original expert leaves the organization, their analytical knowledge remains embedded in validated query pairs. New staff inherit executable knowledge rather than starting from scratch or relying on incomplete documentation.

This cycle breaks the compounding effect identified in the three-pillar framework: turnover no longer erases analytical knowledge because expertise is embedded in validated query pairs rather than individual memory. Low-maturity organizations can accelerate advancement by accumulating validated queries, and technical barriers are reduced because new staff access proven query patterns rather than recreating analytical logic.

1.5 Document Structure

Following this introduction, the paper proceeds through five main sections. The Methodology section describes the narrative review approach, literature search strategy, and source selection criteria. The Framework Development section documents

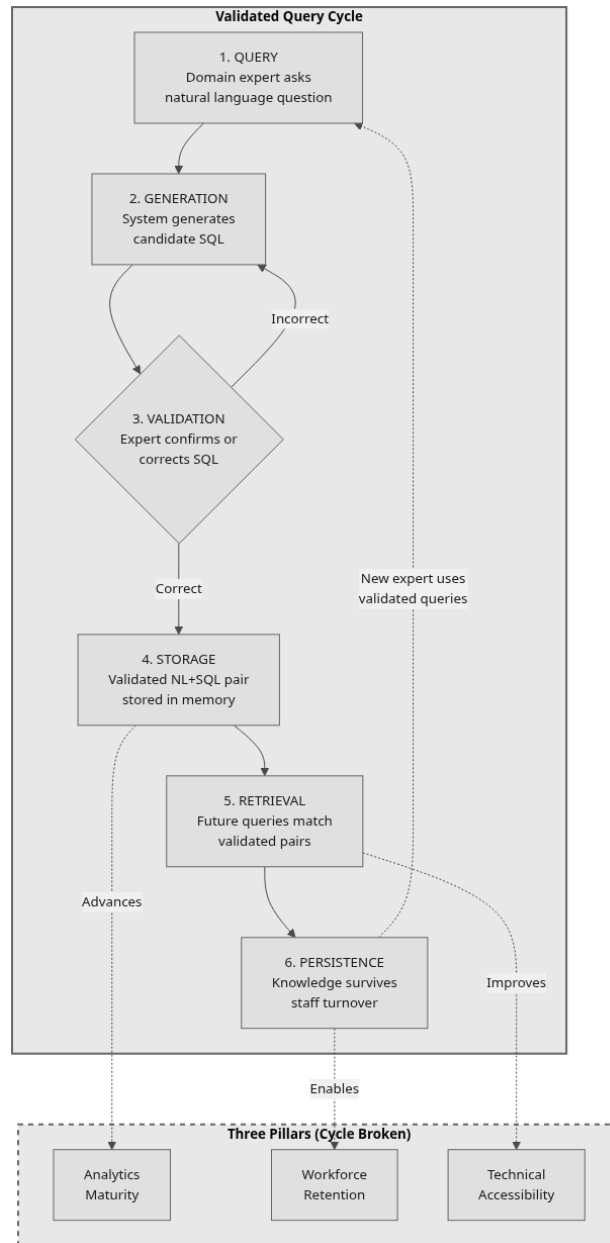


Figure 2: The Validated Query Cycle, shown as six numbered steps in the diagram. (1) Domain experts ask natural language questions, (2) the system generates candidate SQL, (3) experts validate results, (4) validated pairs are stored, (5) future queries retrieve validated knowledge, and (6) expertise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

how the three-pillar framework emerged from the literature and its theoretical grounding. The Literature Review synthesizes evidence across the three pillar domains: natural language to SQL generation, analytics maturity, and workforce dynamics. The Discussion examines implications, limitations, and future research directions. Finally, the Conclusion summarizes the three-pillar analytical framework as this paper’s primary contribution to healthcare informatics literature.

2 Methodology

2.1 Review Approach

This paper employs a narrative review methodology to synthesize evidence across three interconnected domains: healthcare analytics maturity, workforce turnover, and natural language to SQL technologies. Unlike systematic reviews that follow pre-registered protocols with exhaustive searches, narrative reviews provide expert synthesis of relevant literature to construct coherent arguments and identify patterns across diverse evidence sources.

The narrative review approach was selected because:

1. **Integration across domains:** The paper synthesizes evidence from distinct fields (clinical informatics, human resources, natural language processing) that require interpretive integration rather than statistical pooling
2. **Original analytical framework:** The three-pillar framework emerged iteratively from the literature rather than being pre-specified
3. **Heterogeneous evidence types:** The evidence base includes peer-reviewed research, industry reports, and benchmark datasets that cannot be meaningfully combined through meta-analysis

2.2 Literature Search

Literature was identified through multiple channels between January 2023 and December 2025:

Academic Databases:

- Crossref: Cross-disciplinary academic literature, citation metadata
- PubMed: Clinical informatics, healthcare workforce, medical administration
- arXiv: Machine learning and NLP preprints, benchmark studies
- Semantic Scholar: AI and computer science papers, citation analysis

Industry Sources:

- HIMSS: Analytics Maturity Model documentation and industry standards
- Healthcare providers: NHS Trust implementation case studies
- Market research: Precedence Research, Forrester analyst reports
- Technology vendors: Health Catalyst, Oracle, Anthropic technical documentation
- Professional associations: AHIMA/NORC workforce surveys
- Business news: IBM, CNBC coverage of healthcare analytics ventures

Search Concepts:

Search terms were organized around the three-pillar framework:

- Analytics maturity: “healthcare analytics maturity,” “HIMSS AMAM,” “analytics adoption,” “analytics standardization failure,” “low-code healthcare ROI,” “conversational AI platforms”
- Workforce turnover: “healthcare IT tenure,” “IT training time,” “turnover cost salary,” “institutional memory loss,” “knowledge portal,” “knowledge capture,” “SECI model analytics”
- Technical barriers: “NL2SQL healthcare,” “text-to-SQL clinical,” “MIMICSQL,” “EHRSQL,” “NL2SQL accuracy,” “NL2SQL productivity,” “schema discovery,” “PK/FK discovery,” “semantic column matching,” “vector embeddings schema”

Search Results:

Searches across all databases yielded 570 initial results after deduplication. Cross-ref searches for terms including “healthcare analytics maturity,” “HIMSS AMAM,” “NL2SQL clinical,” “knowledge portal,” and “low-code ROI” (2015-current) returned 285 results, of which 15 passed screening. PubMed searches combining workforce terms (“healthcare IT tenure,” “IT training time,” “turnover cost salary”) with analytics terms (“institutional memory,” “analytics adoption,” “knowledge capture”) (2015-current) yielded 142 results with 12 passing screening. arXiv searches in cs.CL and cs.DB categories for “text-to-SQL” combined with technical terms (“MIMICSQL,” “EHRSQL,” “schema discovery,” “PK/FK discovery,” “semantic matching,” “vector embeddings”) (2020-current) produced 71 results with 6 passing screening. Semantic Scholar searches for “NL2SQL healthcare,” “NL2SQL productivity,” “conversational AI clinical,” and “SECI model analytics” (2015-current) returned 72 results with 8 passing screening. The final corpus includes 81 academic and 11 industry sources (92 total).

Figure 3 illustrates the literature selection process, showing progression from initial database search through screening and quality assessment to the final corpus of 92 sources.

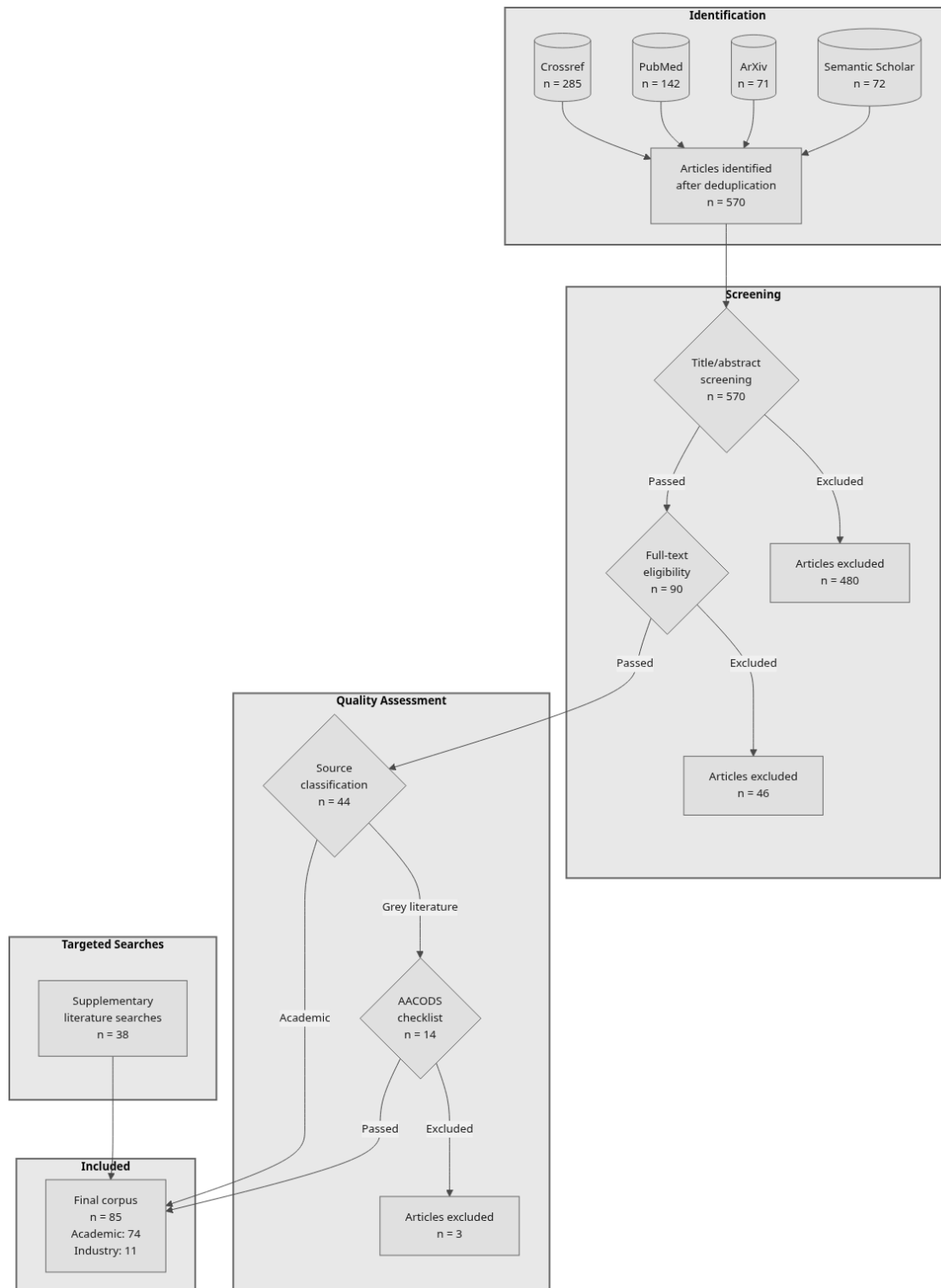


Figure 3: Literature Selection Flow Diagram. The diagram shows the progression from initial database search ($n \approx 570$) through title/abstract screening, full-text review, and quality assessment (AACODS for grey literature) to the final corpus of 92 sources (81 academic, 11 industry). Diagram source available in [figures/literature-flow.mmd](#).

2.3 Source Selection

Sources were selected based on the following criteria:

Inclusion Criteria:

- Peer-reviewed publications in healthcare informatics, medical informatics, computer science, or health services research
- Industry reports from established healthcare IT organizations (HIMSS, AHIMA, AMIA)
- Publications from 2015-current, with emphasis on 2020-current for rapidly evolving NL2SQL technologies
- English language publications
- Sources with verifiable DOIs, URLs, or institutional attribution

Exclusion Criteria:

- Sources without verifiable attribution or institutional backing
- Vendor marketing materials without independent validation
- Preprints without subsequent peer-reviewed publication (exception: foundational NL2SQL benchmarks where peer review is pending)
- Studies with unverifiable statistics or methodological concerns

2.4 Evidence Synthesis

Evidence was synthesized thematically around the three-pillar framework:

1. **Analytics maturity:** Evidence on HIMSS AMAM adoption, healthcare analytics capabilities, and organizational readiness
2. **Workforce turnover:** Evidence on nursing and IT staff turnover rates, institutional memory loss, and knowledge transfer challenges
3. **Technical barriers:** Evidence on NL2SQL benchmarks, healthcare-specific NLP challenges, and low-code implementation patterns

This framework emerged iteratively from the literature rather than being pre-specified, consistent with narrative review methodology.

2.5 Grey Literature Quality Assessment

Grey literature sources were assessed using the AACODS checklist (18), which evaluates Authority, Accuracy, Coverage, Objectivity, Date, and Significance. Sources with vendor sponsorship were retained when no independent alternative existed but flagged in-text. Table 1 summarizes the assessment.

Table 1: AACODS Assessment of Industry Sources

Source	Authority	Accuracy	Coverage	Objectivity	Date	Significance	Include
[11] HIMSS AMAM	High [†]	Verifiable	Global	High	2024	High	Yes
[12] Snowdon/HIMSS	High [‡]	Verifiable	N/A	High	2024	Medium	Yes
[13] Health Catalyst	Medium [§]	Unverifiable	US	Low	2020	Medium	Yes*
[14] Berkshire NHS	High [¶]	Verifiable	Single site	High	2024	High	Yes
[15] Forrester/Microsoft	Medium	Unverifiable	Enterprise	Low [◇]	2024	Medium	Yes*
[16] Oracle	Low [§]	Unverifiable	N/A	Low	2024	Low	Yes*
[17] Precedence Research	Medium [#]	Unverifiable	Global	Medium	2024	Medium	Yes
[18] Anthropic	Medium [§]	Verifiable	N/A	Medium	2025	Low	Yes
[19] IBM Newsroom	High ^{**}	Verifiable	N/A	High	2022	High	Yes
[110] CNBC/Haven	High ^{**}	Verifiable	N/A	High	2021	High	Yes
[111] AHIMA/NORC	High ^{††}	Verifiable	US	High	2023	High	Yes

[†]Industry standards body. [‡]HIMSS officer. [§]Vendor. [¶]NHS trust. ^{||}Analyst firm. [#]Market research. ^{**}Journalism.

^{††}Professional association + academic. [◇]Sponsor. *Vendor sponsorship or low objectivity noted in manuscript text.

2.6 Methodological Limitations

This narrative review has inherent limitations:

- **Non-exhaustive search:** Literature identification was selective rather than exhaustive; relevant studies may have been missed
- **Limited formal quality assessment:** Grey literature sources were assessed using the AACODS checklist; however, no standardized quality assessment tool (e.g., GRADE, Cochrane Risk of Bias) was applied to peer-reviewed sources, as these tools are designed for clinical intervention studies rather than narrative reviews
- **Single-coder bias risk:** Literature screening, data extraction, and thematic analysis were performed by a single author without independent verification. This introduces potential selection and interpretation bias that would be mitigated in systematic reviews through dual-coder protocols with inter-rater reliability assessment
- **Post-hoc selection criteria:** Inclusion and exclusion criteria were refined during the review process rather than pre-registered
- **No protocol registration:** This review was not registered in PROSPERO or similar registries
- **Dated workforce statistics:** The primary healthcare IT turnover statistic (34% annually) derives from Ang and Slaughter’s 2004 study (3). While recent surveys confirm workforce challenges persist (1) and contemporary evidence suggests the situation may have worsened (55% intent to leave among public health informatics specialists (19)), no study has directly replicated the 2004 tenure measurement methodology. Future research should address this methodological gap

These limitations are balanced against the strengths of narrative review methodology: ability to synthesize heterogeneous evidence types across disciplinary boundaries, flexibility to pursue emerging themes, and capacity to construct novel analytical frameworks that illuminate connections between previously disconnected research domains.

3 Framework Development and Validation

This paper’s primary contribution is the three-pillar analytical framework for understanding healthcare analytics challenges: (1) analytics maturity gaps, (2) workforce turnover and institutional memory loss, and (3) technical barriers in natural language to SQL generation. This section documents the framework’s development process and theoretical grounding.

3.1 Framework Development Process

The three-pillar framework emerged through iterative analysis of the literature corpus. Initial review identified numerous disconnected research streams: NL2SQL technical advances, HIMSS maturity models, healthcare workforce turnover studies, knowledge management theory, and healthcare IT implementation case studies. These appeared as isolated topics until thematic analysis revealed recurring patterns of interdependence.

The framework development followed these steps:

1. **Theme Extraction:** Systematic coding of 92 sources identified recurring themes across technical, organizational, and workforce dimensions
2. **Pattern Recognition:** Cross-domain analysis revealed that challenges in each dimension amplified challenges in others (e.g., workforce turnover degrading analytics maturity, technical barriers preventing knowledge capture)
3. **Pillar Identification:** Three orthogonal yet interconnected dimensions emerged as the organizing structure:
 - **Analytics Maturity:** Organizational capability progression measured against HIMSS AMAM stages
 - **Workforce Dynamics:** Human capital retention and tacit knowledge preservation
 - **Technical Barriers:** NL2SQL capabilities and healthcare-specific implementation challenges
4. **Framework Validation:** Pillar structure tested against all 92 sources to confirm comprehensive coverage without significant gaps

3.2 Theoretical Grounding

The three-pillar framework aligns with established models in healthcare informatics and knowledge management:

The HIMSS Analytics Maturity Assessment Model (2) provides organizational benchmarks but does not explicitly address workforce knowledge retention. The Data-Information-Knowledge-Wisdom (DIKW) hierarchy explains the progression from raw data to actionable insight, but standard formulations do not address institutional memory loss. The three-pillar framework synthesizes these perspectives, positioning workforce dynamics as the critical enabler connecting data access (analytics maturity) with organizational wisdom (knowledge preservation).

Table 2: Framework Alignment with Established Models

Three Pillars	HIMSS AMAM Alignment	DIKW Hierarchy	Knowledge Management
Analytics Maturity	Stages 0-7 Progression	Data → Information	Organizational learning
Workforce Dynamics	Implicit in Advanced Stages	Knowledge (tacit) → Wisdom	Tacit knowledge transfer
Technical Barriers	Stage 6-7 Requirements	Information → Knowledge	Knowledge Codification

3.3 Framework Scope and Limitations

The framework is descriptive rather than prescriptive; it provides an analytical lens for understanding healthcare analytics challenges but does not mandate specific solutions. Future research should empirically validate pillar interdependencies through longitudinal organizational studies and develop quantitative metrics for framework dimensions.

4 Literature Review: Evidence Across the Three Pillars

This narrative review synthesizes evidence across the three-pillar framework domains: natural language to SQL generation (technical barriers), healthcare analytics maturity, and workforce dynamics. Drawing from peer-reviewed research, industry reports, and benchmark datasets identified through the methodology described in Section 2 (Methodology), we document the current state of each pillar and reveal interconnections. Analysis reveals three critical findings: (1) natural language to SQL generation has evolved significantly but faces healthcare-specific challenges requiring specialized solutions, (2) healthcare analytics maturity remains low with most organizations struggling at basic stages, and (3) healthcare workforce turnover creates institutional memory loss that traditional approaches fail to address. Evidence across these three domains reveals significant interconnections and compounding effects that the three-pillar framework synthesizes.

4.1 Current State of Natural Language to SQL Generation

4.1.1 Evolution and Technical Advances

Recent systematic reviews document the rapid evolution of natural language to SQL (NL2SQL) technologies. Ziletti and D’Ambrosi (20) demonstrate that retrieval augmented generation (RAG) approaches significantly improve query accuracy when applied to electronic health records (EHRs), though they note that “current language models are not yet sufficiently accurate for unsupervised use” in clinical settings; this assessment, based on 2024 models, has been challenged by late-2025 benchmarks showing GPT-5 exceeds physician baselines on standardized medical reasoning tasks (21), (22), though human oversight remains recommended for clinical safety. Their work on the MIMIC-3 dataset shows that integrating medical coding steps into the text-to-SQL process improves performance over simple prompting approaches.

Benchmarking studies from 2024 (23), (24) examining LLM-based systems for healthcare identify unique challenges: medical terminology, characterized by abbreviations, synonyms, and context-dependent meanings, remains a barrier to accurate query generation. Evaluations of GPT-4 and Claude 3.5 showed 69-73% accuracy on clinical tasks; however, late-2025 models demonstrate substantial improvements. GPT-5 achieves over 80% accuracy on neurosurgical board examinations and surpasses physician performance on multimodal medical reasoning benchmarks by 15-29% (21). On healthcare-specific NL2SQL tasks, GPT-5 achieves 64.6% execution accuracy on the MIMICSQL dataset (25), while the HealthBench benchmark (developed with 262 physicians across 26 specialties) shows GPT-5 hallucination rates of 0.7-1.0%, representing a 4-6x improvement over previous models (22).

4.1.2 Healthcare-Specific Challenges

The literature consistently identifies domain-specific obstacles in healthcare NL2SQL implementation. A systematic review of NLP in EHRs (26) found that the lack of annotated data, automated tools, and other challenges hinder the full utilization of NLP for EHRs. The review, following PRISMA guidelines, categorized healthcare NLP applications into seven areas, with information extraction and clinical entity recognition proving most challenging due to medical terminology complexity.

Wang et al. (27) demonstrate that healthcare NL2SQL methods must move beyond the constraints of exact or string-based matching to fully encompass the semantic complexities of clinical terminology. This work emphasizes that general-purpose language models fail to capture the nuanced relationships between medical concepts, diagnoses codes (ICD), procedure codes (CPT), and medication vocabularies (RxNorm).

4.1.3 Promising Approaches and Limitations

Recent advances show promise in addressing these challenges. The TREQS/MIMIC-SQL dataset development (27) and EHRSQL benchmark (28) provide question-SQL pairs specifically for healthcare, featuring questions in natural, free-form language. Multi-modal benchmarks such as SM3-Text-to-Query (29) extend evaluation beyond SQL to support multiple query languages across diverse medical data representations. This approach acknowledges that healthcare queries often require multiple logical steps: population selection, temporal relationships, aggregation statistics, and mathematical operations.

Healthcare-specific benchmarks continue to evolve alongside model capabilities. The 2024 MedAgentBench evaluation found Claude 3.5 Sonnet achieved 69.67% success rate on medical agent tasks (23), (24); subsequent 2025 benchmarks show GPT-5 significantly exceeding these results, with the SCARE benchmark (30) providing 4,200 EHR question-SQL pairs across MIMIC-III, MIMIC-IV, and eICU databases specifically designed to evaluate post-hoc safety mechanisms for clinical text-to-SQL deployment. Graph-empowered approaches combining LLMs with structured knowledge representations achieve 94.2% execution accuracy on MIMICSQL (31), demonstrating that domain-specific architectural innovations can substantially outperform general-purpose models. While these advances narrow the gap between benchmark performance and clinical readiness, domain-specific challenges in medical terminology and complex clinical reasoning remain active research areas.

4.1.4 Productivity and Efficiency Evidence

Emerging research documents quantifiable productivity gains from NL2SQL implementations. In healthcare settings, organizations implementing natural language interfaces report a 63% increase in self-service analytics adoption among non-technical staff and a 37% reduction in time spent on data retrieval tasks (32). Business analysts using these interfaces spend 42% more time on analysis rather than query construction (32).

Clinical-specific natural language interfaces demonstrate significant efficiency improvements. Criteria2Query, a natural language interface for clinical database cohort definition, achieves fully automated query formulation in an average of 1.22 seconds per criterion, enabling researchers to query EHR data without mastering database query languages (33). The system has evolved through three generations: the original rule-based approach (33), a human-machine collaboration version, and Criteria2Query 3.0, which leverages GPT-4 to generate sharable cohort identification queries against OMOP-CDM formatted databases (34). User studies show NL2SQL systems reduce query completion times by 10-30% compared to traditional SQL plat-

forms while improving accuracy from 50% to 75%, with users recovering from errors 30-40 seconds faster (35).

The most substantial productivity gains appear in multimodal interfaces. Research on speech-driven database querying demonstrates users can specify SQL queries with an average speedup of 2.7x (up to 6.7x) compared to traditional input methods, with user effort reduced by a factor of 10x to 60x compared to raw typing (36). Healthcare-specific natural language query systems show dramatic improvements: a clinical data analytics language (CliniDAL) reduced complex query formulation from “many days” with SQL to “a few hours” with natural language, with expert users describing SQL as “very tedious and time-consuming” for the same analytical tasks (37). NLP-driven data entry systems have achieved 33% time reduction with 15% accuracy improvement in clinical research settings (38). Healthcare-specific NL2SQL models such as MedT5SQL achieve 80.63% exact match accuracy on the MIMICSQL benchmark, demonstrating that domain-adapted language models can effectively translate natural language to SQL for clinical databases (39). These metrics provide peer-reviewed evidence that complements vendor-sponsored efficiency claims.

Code modernization principles directly inform these productivity gains. Foundational work on natural language interfaces to databases (8) established that modular, decoupled architecture enables effective NL access to legacy systems, a design principle applied across subsequent research (e.g., (40)). Modern implementations demonstrate that retrieval-augmented generation (RAG) approaches reduce specialized training requirements by 87.4% compared to traditional querying methods while achieving 92.3% accuracy in interpreting business-specific terminology from legacy mainframe records (41). This convergence of code modernization and natural language interface technologies arises because both rely on the same underlying large language models (9), (10), suggesting that organizations investing in either capability simultaneously advance both.

4.2 State of Healthcare Analytics Maturity

4.2.1 Low Organizational Maturity

The Healthcare Information Management Systems Society (HIMSS) Analytics Maturity Assessment Model (AMAM) provides the industry standard for measuring analytics capabilities. Recent data reveals a concerning state of analytics maturity in healthcare organizations globally (2). The newly revised AMAM24 model, launched in October 2024, represents a significant evolution from the original framework.

Snowdon (42), Chief Scientific Research Officer at HIMSS, emphasizes that “analytics as a discipline has changed dramatically in the last five to 10 years,” yet healthcare organizations struggle to keep pace (4). Research confirms healthcare’s adoption

of analytics often lags behind other sectors such as retail and banking, partly due to the complexity of implementing new technology in clinical environments (4), (43). The newly revised AMAM model shifts focus from technical capabilities to outcomes, measuring the real impact of analytics on patient care, system-wide operations, and governance.

Quantitative evidence links organizational maturity to patient outcomes through two related pathways. First, EMR adoption maturity provides foundational infrastructure: cross-sectional studies using the HIMSS Electronic Medical Record Adoption Model (EMRAM) demonstrate that hospitals with advanced EMR adoption (levels 6-7) have 3.25 times higher odds of achieving better Leapfrog Group Hospital Safety Grades compared to hospitals at EMRAM level 0, with significantly reduced infection rates and fewer adverse events (44). Similarly, high-maturity hospitals have 1.8 to 2.24 times higher odds of achieving higher patient experience ratings (45). Second, analytics capabilities build on this digital foundation: big data analytics capabilities, combined with complementary organizational resources and analytical personnel skills, improve readmission rates and patient satisfaction (46), while poor-quality data results in diagnostic errors, ineffective treatments, and compromised patient care (47). Note that EMRAM measures EMR adoption stages rather than analytics maturity directly; robust digital infrastructure is a prerequisite for analytics, but the AMAM model addresses the analytics-specific capability gap. However, evidence explicitly linking the new AMAM framework to outcomes remains sparse. Studies relying on older proxies yield mixed results: while some align digital maturity with lower staff turnover and reduced errors (48), others find no significant association with readmission rates (49) or mortality (50), suggesting that maturity alone is insufficient without workforce stability.

4.2.2 Barriers to Analytics Adoption

A systematic literature review of big data analytics in healthcare by Kamble et al. (51) identifies critical barriers to analytics adoption. The study reveals that healthcare enterprises struggle with technology selection, resource allocation, and organizational readiness for data-driven decision making.

Health Catalyst's Healthcare Analytics Adoption Model (52), a vendor-produced framework, corroborates these findings, documenting that most healthcare organizations remain at Stages 0-3, characterized by:

- Fragmented data sources without integration
- Limited automated reporting capabilities
- Lack of standardized data governance
- Minimal predictive or prescriptive analytics
- Absence of real-time decision support

4.2.3 The Analytics Skills Gap

The literature consistently identifies workforce capabilities as a primary constraint. Healthcare organizations face mounting challenges in extracting meaningful insights from the vast amount of unstructured clinical text data generated daily (26). There is an acknowledged problem in health services where organizations cannot make good use of available data due to a deficit in skilled analysts across all sectors and levels (5). Organizations face critical challenges in recruiting and retaining professionals with the right analytical skills, while the need for big data specialists with analytical capabilities continues to grow (6). Traditional approaches to analytics require extensive technical expertise and time that healthcare professionals typically lack, creating a fundamental barrier to analytics adoption (1).

4.2.4 Data Quality as a Barrier to Analytics Maturity

Beyond workforce constraints, data quality represents a fundamental barrier preventing healthcare organizations from advancing their analytics capabilities. Research consistently demonstrates that data quality is both a prerequisite for and a dimension of analytics maturity; organizations cannot progress to higher maturity stages without first addressing data quality issues (53). Multiple maturity frameworks, including the Healthcare Data Quality Maturity Model (HDQM2) and the Data Analytics Maturity Assessment Framework (DAMAF), explicitly incorporate data quality as a core assessment dimension (54,55). A cross-industry survey found that data management and quality issues, including lack of documentation, accuracy, and consistency, continue to challenge analytics organizations even as they mature, with the specific challenges shifting from integration to privacy and documentation concerns at higher maturity levels (56).

The prevalence of data quality issues in healthcare databases is substantial. A study of the National Cancer Database found missing data rates ranging from 39.7% for prostate cancer to 71.0% for non-small cell lung cancer (57). Medical registry data shows 2.0% to 4.6% inaccurate records and 5% to 6% incomplete data (58). Duplicate patient records affect 0.16% to 15.47% of records across healthcare institutions, with wide variation in management practices (59). Analysis of Medicaid claims data found that 9.74% of data cells contained defects, with issues frequently remaining obscure due to separation between data users and producers (60).

Critically, automated data quality tools alone are insufficient for healthcare data. Research demonstrates that clinical domain expert involvement is necessary at every stage of the data pipeline, including curation, cleaning, and analysis (61). Automated tools fail to detect context-dependent errors such as mutually exclusive values, definitional differences between institutions, or plausibility issues that require clinical

judgment (62). Even successful automation requires embedding clinical knowledge; generic automated cleaning tools from other domains are unsuitable for clinical data, which requires variable-specific rules based on clinical knowledge of normal ranges, extreme values, and clinical contexts (63).

Compounding these challenges, healthcare database schemas are frequently undocumented or poorly documented. Commercial EMR systems use proprietary data models that are not publicly available, requiring “detective work” and reverse-engineering for research data integration (64,65). A systematic review found that metadata models are often too complicated for healthcare professionals without specific IT skills, resulting in rare usage and poorly maintained documentation (66). Poor chart documentation by healthcare providers propagates downstream to administrative data quality issues (67). Most critically, documentation knowledge is lost with staff changes: decisions based on poorly documented data represent significant costs and risks, with explicit identification of “loss of information with staff changes” as a key vulnerability (68).

This creates a compounding effect across the three pillars: low-maturity organizations have worse data quality and documentation, which requires domain expertise to address, but that expertise is lost through workforce turnover, further degrading data quality and preventing maturity advancement.

4.3 Healthcare Workforce Turnover and Knowledge Loss

4.3.1 Turnover Rates and Financial Impact

Multiple meta-analyses provide comprehensive data on healthcare workforce turnover. Wu et al. (17) found a pooled prevalence of nurse turnover at 18% (95% CI: 11-26%), with rates varying from 11.7% to 46.7% across different countries and settings. Ren et al. (69) corroborated these findings with a global nurse turnover rate ranging from 8% to 36.6%, with a pooled rate of 16% (95% CI: 14-17%).

The financial implications are substantial. Massingham (70) measured the impact of knowledge loss in a longitudinal study, finding that the total financial cost to address problems caused by knowledge loss reached three times the organization’s annual salary budget, including increased training costs, productivity losses, and project delays. Healthcare-specific evidence quantifies replacement costs in absolute terms: nurse turnover costs 1.2-1.3 times the registered nurse’s annual salary, with the highest cost categories being vacancy, orientation/training, and new employee productivity loss (71); replacing a primary care clinician costs healthcare organizations over \$500,000 due to lost revenue and recruiting expenses (72); while physician replacement can reach up to \$1 million per departure, with national annual costs estimated at \$4.6 billion (73). Vendor analysis from Oracle (74) corroborates these findings,

documenting turnover costs at 0.5-2.0 times annual salary with knowledge-intensive positions reaching the higher end.

Technical and analytics staff face even more severe turnover challenges. In their 2004 study, Ang and Slaughter (3) found that IT professionals at healthcare provider institutions (where IT serves as a support function rather than core business) had average tenure of just 2.9 years, implying annual turnover of 34% (calculated as $1/2.9$ years), the highest rate among all IT organization types studied at that time. This compared unfavorably to the 9.68-year average for IT managerial positions overall. While this data is now two decades old, contemporary evidence suggests the turnover challenge persists or has worsened. A 2025 analysis of nationally representative US survey data ($n=44,732$) found that 55% of public health informatics specialists intended to leave their positions (19). The 2023 AHIMA/NORC workforce survey found that 66% of health information professionals report persistent staffing shortages, with 83% witnessing increased unfilled positions over the past year (1).

The knowledge loss implications are substantial. Research documents significant time-to-productivity requirements across healthcare IT roles: basic EHR training requires 8 hours to 2 months for end-users, while health information workforce development demands 18 months to 2 years for specialized roles (75). International Medical Informatics Association recommendations specify a minimum of 1 year (60 ECTS credits) for biomedical and health informatics specialists (76), with personalized EHR training programs requiring 6 months of blended instruction to achieve meaningful competency improvements (77). For IT developers and specialists, research suggests up to 3 years are required to become fully fluent in complex healthcare IT projects (78). Combined with the 2.9-year average tenure, healthcare IT professionals may operate at full productivity for only approximately two years before departing, and, in the case of IT developers, are likely to leave before reaching full fluency. This creates a perpetual cycle where organizations lose experienced staff before fully recouping their training investment.

The impact on care continuity is well-documented. Clinical handover disruption is internationally recognized as a patient safety priority because it represents a fundamental disruption to continuity of care and is prone to errors (79). Empirical studies demonstrate that nursing unit turnover reduces workgroup learning and is associated with increased patient falls, medication errors, and reduced patient satisfaction (80). International evidence links high workforce turnover to poorer continuity of care, particularly in remote health services, with measurable outcomes including increased hospitalizations and years of life lost (81). When senior executives and knowledge workers depart, organizations experience “corporate memory loss” that undermines organizational continuity and effectiveness (82).

4.3.2 Institutional Memory Loss

The concept of institutional memory in healthcare has received increasing attention. Institutional memory encompasses the collective knowledge, experiences, and expertise that enables organizational effectiveness. Healthcare organizations typically lack formal mechanisms for knowledge preservation, relying instead on person-to-person transfer that fails during rapid turnover. Cultural and regulatory obstacles for data sharing further limit the ability of healthcare organizations to achieve the full potential of their data assets (83).

When experienced analysts, clinical informatics professionals, or data-savvy clinicians leave, they take with them irreplaceable knowledge about data definitions, business rules, analytical approaches, and organizational context. Research on tacit knowledge transfer provides strong evidence that this knowledge is inherently difficult to document through traditional means. Empirical studies demonstrate that learning related to tacit knowledge is often not captured in formal post-project review reports (84), and conventional mechanisms such as documents, blueprints, and procedures fail because tacit knowledge is not easily codified (85). Research across multiple industries consistently shows that written reports and databases fail to convey key learning from expert teams (86), while experts often lack the skills, motivation, or time to document their expertise, and even when documentation is attempted, essential aspects are lost due to lack of shared experience between experts and novices (87).

4.3.3 Inadequacy of Traditional Approaches

The literature demonstrates that conventional knowledge management approaches fail in healthcare contexts (83,88):

- Traditional knowledge transfer mechanisms show limited effectiveness
- Organizations struggle to capture and maintain analytical expertise
- Security concerns and employee resistance to change slow the pace of information system acceptance (88)
- Person-to-person knowledge transfer fails during rapid turnover cycles

4.4 Integration of Evidence: Synthesis Across Three Pillars

4.4.1 Bridging Technical and Domain Expertise

At its core, bridging technical and domain expertise serves a fundamental patient care objective: enabling clinical professionals to access and act on data that improves care

quality. The convergence of evidence from these three domains reveals compounding effects that the three-pillar framework synthesizes. Natural language interfaces directly address the technical barriers identified in the literature by eliminating the need for SQL expertise while preserving the sophisticated query capabilities required for healthcare data.

Low-code platforms and conversational AI represent complementary approaches to reducing technical barriers in healthcare analytics. Low-code platforms provide visual development environments that accelerate application development and reduce coding requirements, while conversational AI enables natural language interaction with data systems. These approaches share core benefits: both democratize access by enabling non-technical users to perform complex analyses previously requiring data scientist intervention, both accelerate development cycles by abstracting technical complexity, and both produce more self-documenting systems where business logic is expressed in accessible formats rather than specialized code. Evidence from low-code implementations thus informs conversational AI adoption, as both address the same fundamental barrier: the gap between clinical expertise and technical capability.

4.4.2 Knowledge Preservation Through Embedded Systems

The literature suggests that effective knowledge preservation requires active, embedded systems rather than passive documentation. When organizations choose to implement AI-based platforms, these can serve as organizational memory systems by:

- Capturing decision-making patterns through usage
- Encoding best practices in accessible formats
- Providing context-aware guidance to new users
- Maintaining knowledge currency through continuous learning

These principles align with conversational AI approaches that embed institutional knowledge within the AI model itself, making expertise permanently accessible regardless of staff turnover.

4.4.3 Empirical Support for Barrier-Reducing Technologies

Academic research provides growing evidence for both conversational AI and low-code approaches in healthcare, technologies that share the goal of reducing technical barriers to data-driven decision making. A foundational systematic review of AI conversational agents in healthcare (89) established that such systems reduce burden on healthcare resources and save providers' time, though the review identified a need

for more rigorous quantitative validation. Subsequent RCT-based systematic reviews provide this evidence: a meta-analysis of conversational agent interventions reported mean task completion rates of 83% (range 40-100%) across healthcare applications (90). Real-world validation at scale comes from a study of conversational AI across nine NHS mental health services involving 64,862 patients, demonstrating reduced clinician assessment time, shorter patient wait times, and lower dropout rates (91). On the clinical AI side, Sezgin et al. (92) demonstrated that GPT-3-powered chatbots can reduce overhead at clinics, while Jiao et al. (93) found AI adoption leads to cost savings through improved service delivery and shorter hospitalization lengths. Dai and Abramoff (94) explain that AI generates predictions affordably, enabling earlier care that potentially prevents costly interventions.

Low-code implementations provide parallel evidence for the benefits of barrier reduction. Berkshire Healthcare NHS Trust (95) reports over 800 “citizen developers” (and over 1,600 total users) now creating solutions using Microsoft Power Platform. The NHS program demonstrates that healthcare professionals without IT expertise can use low-code tools to create custom solutions and apps, streamlining operations and enabling data-driven decisions. This evidence supports the broader principle that reducing technical barriers, whether through visual development or natural language interfaces, enables healthcare domain experts to leverage data directly. A systematic literature review of 17 peer-reviewed papers identified cost and time minimization as the most frequently discussed benefits of low-code development, with healthcare among the primary implementation domains (96). Controlled experiments quantify these benefits: a comparative study of traditional versus low-code development for a healthcare cognitive rehabilitation system found low-code required 47.5 hours versus 888 hours for traditional development, representing a 94.63% reduction in effort (97). Industry-sponsored research from Forrester (98) projects 206% three-year ROI from low-code implementations; peer-reviewed studies report similar findings, with healthcare institutions achieving 177% ROI over 36 months while reducing development time by 67% and technical resource requirements by 58% (99), and small healthcare clinics achieving 250% cumulative ROI over three years (100).

Healthcare-specific studies show concrete benefits across both approaches: Pennington (101) found AI in revenue cycle management accelerated payment cycles from 90 days to 40 days, while Atobatele et al. (102) documented how low-code platforms enable non-technical staff to build applications, leading to efficiency gains. Rapid application development using low-code characteristics enabled an mHealth app for COVID-19 remote care that saved 2,822 hospital bed-days for 400 enrolled patients (103). These findings collectively demonstrate that technologies enabling non-technical users to interact with complex systems, whether through visual interfaces or natural language, produce measurable organizational benefits.

4.5 Implications for Healthcare Organizations

4.5.1 Framework Alignment with Industry Trajectories

Applied to recent industry literature, the three-pillar framework highlights how barrier-reducing technologies track with broader healthcare analytics trajectories. The revised HIMSS AMAM model (2) emphasizes AI readiness and governance frameworks, and conversational interfaces for analytics can be understood as one illustrative application of these themes: they aim to democratize access to data while preserving organizational controls, rather than constituting a prescriptive pathway to maturity advancement.

4.5.2 ROI Evidence Across Barrier-Reducing Approaches

Academic research documents multiple pathways to ROI for barrier-reducing technologies in healthcare. Conversational AI implementations show direct benefits: Jiao et al. (93) found that AI-driven efficiency gains, including shorter hospitalization lengths, translate into financial and operational benefits for healthcare providers; Pennington (101) documented that AI in revenue cycle management accelerated payment cycles from 90 to 40 days, improving cash flow; and Sezgin et al. (92) proposed chatbot implementations that reduce clinic overhead.

Low-code platform ROI provides analogous evidence for the value of technical barrier reduction. Industry-sponsored research from Forrester (98) projects 206% three-year ROI from Power Platform implementations. Peer-reviewed studies corroborate these findings: a systematic review identified cost and time reduction as the most frequently discussed benefits across 17 studies (96), healthcare institutions report 177% ROI over 36 months with 67% faster development (99), and small healthcare clinics document 250% cumulative three-year ROI (100). While low-code and conversational AI differ in implementation approach, both generate returns through the same mechanism: enabling domain experts to accomplish tasks previously requiring specialized technical staff. Market research supports continued investment in accessible analytics: Precedence Research (104) projects the healthcare analytics market to grow from \$64.49 billion in 2025 to \$369.66 billion by 2034 (21.41% CAGR).

4.5.3 Knowledge Preservation as Risk Factor

The literature emphasizes that institutional memory loss represents an existential risk to healthcare analytics programs, particularly when critical analytical practices remain tacit and concentrated in a small number of experts. Within our three-pillar framework, this risk appears as a compounding mechanism: workforce turnover

erodes tacit expertise, low analytics maturity limits organizations' ability to encode that expertise, and technical barriers constrain efforts to make encoded knowledge broadly accessible. Effective knowledge preservation therefore requires mechanisms that transform tacit analytical knowledge into encoded, shareable, and routinely accessible artifacts. This requirement aligns with Nonaka's SECI model (Socialization, Externalization, Combination, Internalization), which describes organizational knowledge creation as a continuous dialogue between tacit and explicit knowledge (105). Recent research demonstrates that AI tools, including conversational interfaces, can enhance all four SECI stages, particularly facilitating the externalization process where tacit analytical knowledge becomes explicit, queryable forms (106). This theoretical foundation supports embedding organizational knowledge in systems rather than individuals, ensuring continuity despite workforce turnover.

4.6 Gaps in Current Literature

Despite substantial evidence supporting conversational AI in healthcare analytics, several research gaps persist:

1. **Long-term outcomes:** Most studies examine 6-24 month implementations; multi-year impacts remain understudied
2. **Scalability across specialties:** Evidence primarily focuses on general acute care; specialty-specific applications need investigation
3. **Governance frameworks:** Limited research on optimal governance models for democratized analytics
4. **Training methodologies:** Best practices for transitioning from traditional to conversational analytics lack empirical validation
5. **Integration patterns:** Architectural guidance for incorporating conversational AI into existing healthcare IT ecosystems remains sparse
6. **Long-term productivity tracking:** While peer-reviewed studies now document immediate productivity gains (63% self-service adoption increase, 37% data retrieval time reduction, 10-30% query completion time improvement (33), (32), (36), (35)), longitudinal studies tracking sustained productivity improvements over multiple years remain limited
7. **Citizen developer productivity methodology:** No validated healthcare-specific instrument exists for measuring citizen developer productivity. While Berkshire NHS reports 800+ citizen developers (95), the methodology for quantifying their productivity contributions lacks standardization across studies
8. **AMAM-specific outcome evidence:** The HIMSS Analytics Maturity Assessment Model (AMAM) was released in October 2024; existing outcome studies linking maturity stages to patient outcomes use the older EMRAM (EHR adoption) model (44,45). As of this review, AMAM-specific outcome studies remain

very limited, providing only emerging evidence for analytics maturity (as distinct from EHR adoption) impact on outcomes

4.7 Why the Problem Persists

Despite clear evidence of healthcare’s analytics challenges and available technology, the problem remains unsolved. Analysis of market dynamics reveals three structural barriers:

4.7.1 Failed Standardization Approaches

Large-scale efforts to standardize healthcare data and analytics have consistently encountered fundamental barriers. Academic research identifies a persistent tension between achieving short-term institutional solutions and pursuing long-term global interoperability, with standardization complexity arising from diverse community interests and technical issues (16). Data standardization faces three primary technological obstacles: metadata uncertainties, data transfer challenges, and missing data, compounded by legacy data collection methods that have created a “patchwork” of inconsistent organizational practices (107).

These challenges manifest in clinical practice through workflow variability. Even within the same institution, clinical workflows vary significantly, and transitions to standardized systems often cause profound disruptions to existing processes (108). At the institutional level, data fragmentation across different organizations creates barriers to linkage, access, and care continuity, while governance issues including unclear responsibilities and weak collaboration compound the problem (109).

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 systems where machines learn from structured data but physicians work with unstructured, complex clinical information (111). 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.

These observations represent documented market events; however, establishing causal mechanisms between organizational strategies and interoperability outcomes requires controlled empirical research beyond this review’s scope. The patterns noted here warrant further investigation through rigorous organizational studies.

4.7.2 Deployment Constraint Mismatch

Healthcare organizations increasingly require solutions functional in secure, air-gapped environments due to regulatory requirements and data governance policies. General-purpose cloud AI services cannot meet these deployment constraints while simultaneously lacking the institution-specific context necessary for accurate analytics. The fundamental requirement that institutional knowledge must be captured, preserved, and accessed within each organization’s specific environment cannot be addressed by standardized cloud offerings.

These dynamics explain why, despite technological capability, the healthcare analytics maturity gap persists. Solutions must be designed for institution-specific deployment rather than cross-organizational standardization.

5 Discussion

5.1 Strengths of the Evidence Base

The evidence base for the three-pillar framework presents several strengths:

5.1.1 Validated Benchmarking Data

The evidence base includes peer-reviewed benchmarking studies from top venues (NEJM AI, NeurIPS, NAACL) that provide empirical validation of LLM capabilities in healthcare contexts. Studies like MedAgentBench (23) and comprehensive medical LLM evaluations (24) offer reproducible, quantitative performance metrics.

5.1.2 Real-World Implementation Evidence

The Berkshire Healthcare NHS Trust case (95) demonstrates successful low-code adoption in healthcare, with over 800 citizen developers creating solutions. This provides concrete evidence that non-technical healthcare professionals can effectively use these platforms.

5.1.3 Reveals Interconnected Challenges

The framework illuminates how technical barriers, analytics maturity constraints, and institutional memory loss compound each other, explaining why single-pillar interventions often fail. This integrated perspective enables healthcare organizations to understand why addressing one challenge in isolation may not produce lasting improvement.

5.1.4 Strong Economic Justification

The financial evidence is compelling, with Forrester Research (98) documenting 206% three-year ROI from low-code implementations. Market growth projections (104) showing the healthcare analytics market expanding from \$64.49B to \$369.66B by 2034 indicate sustained investment demand.

5.1.5 Honest Assessment of Limitations

The evidence base includes important caveats. Ziletti and D'Ambrosi (20) note that "current language models are not yet sufficiently accurate for unsupervised use," and benchmarking studies (3,24) show significant gaps between benchmark performance and clinical readiness. This honest assessment enables appropriate implementation strategies.

5.2 Limitations and Constraints

Despite strong evidence supporting conversational AI adoption, several limitations must be acknowledged:

5.2.1 Implementation Complexity

Healthcare environments present unique complexity challenges including regulatory requirements, legacy system integration, and change management across diverse

user populations. Implementation timelines reflect this complexity, though low-code approaches compare favorably to traditional analytics infrastructure projects. Healthcare and pharmaceutical organizations face particularly acute legacy modernization challenges, paralleling patterns documented in broader enterprise software contexts (7).

5.2.2 Context-Specific Customization Requirements

Healthcare organizations vary significantly in data structures, clinical workflows, and analytical needs. Evidence suggests that successful implementations require substantial customization to organizational contexts, potentially limiting the applicability of standardized approaches.

5.2.3 Long-Term Outcome Uncertainties

Most studies examine 6-24 month implementations. Questions remain about long-term sustainability, user engagement over extended periods, and the evolution of organizational capabilities beyond initial deployment periods. The research gap analysis in the Literature Review identifies this as a priority area for future investigation.

5.2.4 Governance and Quality Assurance Challenges

Democratizing analytics access creates new challenges in maintaining data quality, analytical rigor, and clinical safety standards. While the evidence shows reduced error rates with conversational AI, healthcare organizations must develop new governance frameworks for managing distributed analytical capabilities.

5.2.5 Specialty-Specific Application Gaps

Evidence primarily focuses on general acute care settings. Applications in specialized domains (oncology, cardiology, mental health) require domain-specific validation and customization that may not generalize from the existing evidence base.

5.2.6 Methodological Considerations

As a narrative review, this paper has methodological limitations distinct from systematic reviews. The non-exhaustive literature search, single-author synthesis, and post-hoc selection criteria may have introduced selection or interpretation bias. No

formal quality assessment tool was applied to included studies. These limitations, documented in detail in the Methodology section, should be considered when interpreting findings. The transparency provided through explicit documentation of search strategies, selection criteria, and synthesis approach enables readers to assess potential biases and evaluate the robustness of conclusions.

5.3 Future Research Directions

The evidence review identifies several priority areas for future investigation:

5.3.1 Short-Term Research Priorities (<1 year)

1. **Reference Implementation Validation:** Empirical validation of NL2SQL approaches using synthetic healthcare data (e.g., Synthea) in reproducible cloud environments, enabling benchmarking against established datasets (EHRSQL, MIMICSQL) without privacy constraints
2. **Schema Discovery for Healthcare Databases:** Research on automated primary/foreign key discovery algorithms applied to healthcare schemas, addressing the complexity of clinical data models
3. **Governance Framework Development:** Research on optimal governance models for democratized analytics

5.3.2 Medium-Term Research Priorities (1-2 years)

1. **Healthcare Terminology Integration:** Development of programmatic approaches for mapping natural language queries to standardized vocabularies (SNOMED CT, LOINC, RxNorm) within NL2SQL pipelines
2. **FHIR/OMOP Interoperability:** Research on reducing ETL burden for OMOP Common Data Model and FHIR transformations, enabling NL2SQL systems to operate across heterogeneous healthcare data standards
3. **Longitudinal Outcome Studies:** Multi-year implementations to assess sustained benefits and organizational evolution
4. **Comparative Effectiveness Research:** Head-to-head comparisons of different conversational AI approaches on healthcare-specific benchmarks

5.3.3 Long-Term Research Priorities (>2 years)

1. **Organizational Transformation Studies:** Research on how conversational AI platforms reshape healthcare organizational capabilities

2. **Clinical Outcome Impact Assessment:** Studies linking improved analytics access to patient care outcomes
3. **Cross-Institution Knowledge Portals:** Investigation of federated approaches enabling knowledge sharing across healthcare organizations while maintaining privacy and security requirements

5.4 Illustrative Application: Knowledge Preservation Mechanisms

To illustrate how the three-pillar framework might inform technology design, we examine the validated query cycle concept introduced earlier. This mechanism differs fundamentally from traditional knowledge management approaches in healthcare. Traditional approaches rely on documentation: analysts write procedures, create data dictionaries, and maintain query libraries. However, documentation suffers from three critical weaknesses: it becomes stale as systems evolve, it captures procedural knowledge but not contextual judgment, and it requires active maintenance that often lapses after staff transitions.

Validated query pairs address each weakness. First, validated pairs are executable: they can be tested against current data to verify continued correctness, unlike static documentation. Second, validated pairs capture the complete mapping from business question to data retrieval logic, embedding the contextual judgment that documentation typically omits (why this join, why this filter, why this aggregation). Third, validation happens at the point of use rather than as a separate maintenance task: every confirmed query becomes a knowledge artifact without additional documentation effort.

This mechanism also differs from traditional query logging or usage analytics. Query logs capture what was asked, but not whether the answer was correct. Validated query pairs capture expert confirmation that the SQL correctly answers the business question. This distinction is critical for institutional memory: organizations need to know not just what queries were run, but which queries produced trusted, verified answers.

Governance requirements for the validated query cycle include: defining who can validate queries (domain expertise requirements), establishing validation workflows (review processes for high-stakes queries), managing query versioning (as schemas evolve), and implementing retrieval policies (when to return exact matches versus inform new generation). Organizations implementing conversational AI platforms should design these governance structures before deployment rather than retrofitting them after knowledge accumulation begins.

5.5 Implications for Healthcare Organizations

The evidence has implications for healthcare leaders considering analytics strategy:

5.5.1 Organizational Assessment Using the Three-Pillar Framework

The three-pillar framework provides a structured approach for organizational self-assessment:

- 1. **Analytics Maturity Assessment:** Where does the organization currently stand on the HIMSS AMAM scale? What capabilities are needed to advance?
- 2. **Workforce Knowledge Audit:** What tacit knowledge resides with individual staff members? How vulnerable is the organization to knowledge loss through turnover?
- 3. **Technical Barrier Inventory:** What technical skills are currently required for data access? Which clinical questions go unanswered due to technical barriers?

5.5.2 Three-Pillar Assessment Rubric

The three-pillar framework enables organizational self-assessment to determine readiness for and potential benefit from NL2SQL and conversational AI interventions. Table 3 provides an evidence-based rubric where each indicator anchors to reviewed literature. Organizations scoring predominantly “Higher Risk” across pillars face compounding challenges that NL2SQL platforms are specifically designed to address: democratizing data access (Technical Barriers), preserving institutional knowledge (Workforce Dynamics), and accelerating maturity advancement (Analytics Maturity).

Table 3: Three-Pillar Organizational Assessment Rubric

Analytics Maturity Indicators:

Indicator	Lower Risk	Moderate Risk	Higher Risk	Evidence
HIMSS AMAM Stage	Stages 5-7: Predictive analytics, AI integration	Stages 3-4: Integrated warehouse, standardized definitions	Stages 0-2: Fragmented data, limited reporting	(2,52)

Indicator	Lower Risk	Moderate Risk	Higher Risk	Evidence
Self-service analytics	Widespread; clinical staff access data directly	Partial; BI tools available but underutilized	None; all analytics require IT intervention	(4,95)
AI/NL interface availability	Natural language query capability deployed	Pilot programs or evaluation underway	No NL2SQL or conversational analytics	(20,27)

Workforce Dynamics Indicators:

Indicator	Lower Risk	Moderate Risk	Higher Risk	Evidence
Annual IT turnover rate	<15%	15-30%	>30% (exceeds 2004 healthcare IT baseline)	(3)
Knowledge concentration	Distributed expertise; documented processes	Partial documentation; some cross-training	Critical expertise held by ≤ 3 individuals	(15,16)
Time-to-productivity	<6 months with structured onboarding	6-18 months	>18 months (specialized health informatics roles)	(75-77)
Tacit knowledge capture	Expertise embedded in systems/AI	Partial documentation exists	Person-dependent; undocumented tribal knowledge	(15)

Technical Barriers Indicators:

Indicator	Lower Risk	Moderate Risk	Higher Risk	Evidence
Data access requirements	Natural language or visual query interfaces	IT queue for complex queries; basic self-service	SQL/technical expertise required for all queries	(4-6)
Interoperability status	Unified data platform; real-time integration	Partial integration; some automated feeds	Fragmented systems; manual reconciliation required	(107,109)
Skills gap severity	Sufficient analysts across departments	Acknowledged deficit with mitigation plans	Critical shortage preventing data utilization	(5,6)

Multi-Pillar Convergence Assessment:

Organizational Profile	Framework Assessment	Implications for Analysis
All pillars Lower Risk	Continuous improvement stance	Monitor for emerging challenges; single-pillar focus may suffice
1 pillar Higher Risk	Isolated challenge	Single-domain intervention may address root cause; watch for spillover effects
2 pillars Higher Risk	Compounding effects present	Framework reveals interconnections requiring multi-dimensional analysis
All 3 pillars Higher Risk	Self-reinforcing degradation cycle	All three dimensions interact; comprehensive organizational assessment warranted

The framework reveals why convergence matters: organizations facing Higher Risk across multiple pillars experience compounding effects where challenges in one domain exacerbate challenges in others. For example, technical barriers that prevent knowledge capture interact with workforce turnover to accelerate institutional mem-

ory loss, which in turn degrades analytics maturity. This multi-pillar perspective explains why single-domain interventions often produce limited results.

5.5.3 Illustrative Application: Implementation Patterns

When organizations choose to apply the framework and evaluate barrier-reducing technologies for potential adoption, implementation evidence suggests several factors influence outcomes:

- **Governance Framework Development:** New policies and procedures for democratized analytics
- **Change Management:** Training and support programs to ensure user adoption
- **Phased Deployment:** Gradual rollout beginning with analytics-savvy early adopters
- **Human Oversight:** Current NL2SQL limitations require maintaining human review of AI-generated outputs (20)

6 Conclusion

This narrative review synthesized evidence across three interconnected domains: natural language to SQL generation, healthcare analytics maturity, and workforce-driven institutional memory loss. The primary contribution is a three-pillar analytical framework that reveals how these challenges interconnect and compound each other.

6.1 What the Framework Reveals

The three-pillar framework illuminates patterns that single-domain analyses miss:

- **Analytics maturity gaps** leave clinical decisions unsupported by available data, and low maturity correlates with higher workforce turnover as staff leave organizations where they cannot accomplish their goals
- **Workforce turnover** (34% annually for healthcare IT staff as of 2004 (3)) causes institutional memory loss that further degrades analytics capabilities, creating a reinforcing cycle
- **Technical barriers** prevent organizations from capturing and preserving analytical knowledge, blocking recovery from either maturity gaps or turnover impacts

These interconnections explain why addressing any single pillar in isolation often fails: improvements in one area erode when the compounding effects from other pillars continue. The framework provides a structured lens for organizational self-assessment.

6.2 Summary of Contributions

This narrative review contributes to healthcare informatics scholarship through:

1. **Three-Pillar Analytical Framework** (Primary Contribution): The framework synthesizes previously disconnected evidence from healthcare analytics maturity, workforce management, and natural language processing research, revealing how these challenges interconnect and compound each other: low maturity accelerates turnover, turnover degrades maturity, and technical barriers prevent recovery from either.
2. **Evidence Synthesis**: We consolidate current evidence on each pillar, providing healthcare organizations with a comprehensive view of analytics maturity benchmarks, workforce turnover impacts, and NL2SQL technical capabilities in a single resource.
3. **Illustrative Application**: By applying established knowledge portal theory (15,16), we describe the validated query cycle as one example of how the framework might inform technology design for institutional memory preservation.

6.3 Key Findings

This review of academic and industry sources establishes several critical findings:

1. **Technical Progress with Limitations**: Natural language to SQL technologies have advanced significantly, with healthcare-specific benchmarks (27,28) demonstrating substantial progress in clinical NL2SQL tasks. However, current models are “not yet sufficiently accurate for unsupervised use” in clinical settings (20), requiring human oversight.
2. **Organizational Need**: Healthcare analytics maturity remains an ongoing challenge, with the revised HIMSS AMAM model (2) emphasizing the need for AI readiness and governance frameworks. Most organizations struggle to advance beyond basic reporting levels.
3. **Workforce Impact**: Healthcare IT staff turnover was measured at 34% in 2004 (3), the highest among IT sectors at that time, and workforce challenges persist today (1). Knowledge loss costs can reach three times annual salary budgets (70), creating need for knowledge preservation approaches.
4. **Implementation Evidence**: Real-world implementations like Berkshire Healthcare NHS Trust (95) demonstrate that low-code platforms can enable 800+ citizen developers in healthcare settings, with academic research documenting significant efficiency improvements and cost reductions (92,93).

6.4 Implications for Organizational Assessment

The evidence synthesis suggests healthcare organizations face decisions that cannot be reduced to simple adoption/rejection binaries. Applying *primum non nocere* comprehensively requires organizational leaders to:

1. **Assess current harm exposure:** Quantify institutional memory loss from turnover, measure time-to-insight for clinical questions, and evaluate analytics capability gaps against organizational needs
2. **Evaluate intervention risks:** Consider NL2SQL accuracy limitations (“not yet sufficiently accurate for unsupervised use” (20)), governance requirements, and implementation complexity
3. **Apply the three-pillar framework:** Use the analytics maturity, workforce turnover, and technical barrier dimensions to structure organizational assessment and prioritization

Throughout this assessment, quality patient care must remain the primary metric. Operational efficiency, cost savings, and technical capabilities are valuable only insofar as they advance healthcare’s fundamental mission.

This framework acknowledges that optimal decisions will vary by organizational context. Healthcare systems with stable analytics teams and mature data infrastructure face different risk profiles than those experiencing rapid turnover and limited analytics capabilities. The evidence does not prescribe universal solutions but provides structured approaches for context-specific evaluation.

6.5 Closing Reflection

Primum non nocere ultimately requires healthcare organizations to make evidence-based judgments about both action and inaction. This review contributes a three-pillar analytical framework to support those judgments, synthesizing evidence on analytics maturity, workforce dynamics, and technical capabilities.

The evidence does not prescribe universal adoption of any technology. Rather, it establishes the scope and interconnection of challenges that organizations must address through whatever means align with their specific contexts, capabilities, and risk tolerances. The ongoing harms documented in this review (institutional memory loss, analytics capability gaps, and technical barriers to data access) merit the same careful consideration as the risks of new technology adoption.

Healthcare’s commitment to avoiding harm is best served by evidence-based evaluation that considers all dimensions of potential benefit and risk. The three-pillar framework offers one structured approach for conducting such evaluations.

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8 Author Contributions

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

9 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.

10 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. The literature search methodology and source selection criteria are documented in the Methodology section.

11 Code Availability

Not applicable. No custom code was developed for this research.

12 Funding

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13 Abbreviations

AACODS: Authority, Accuracy, Coverage, Objectivity, Date, Significance ACO: Accountable Care Organization AI: Artificial Intelligence AMAM: Analytics Maturity Assessment Model CPT: Current Procedural Terminology DAMAF: Data Analytics Maturity Assessment Framework DIKW: Data-Information-Knowledge-Wisdom EHR: Electronic Health Record EMRAM: Electronic Medical Record Adoption Model HDQM2: Healthcare Data Quality Maturity Model HIMSS: Healthcare Information Management Systems Society ICD: International Classification of Diseases IT: Information Technology LLM: Large Language Model NL2SQL: Natural Language to SQL RAG: Retrieval-Augmented Generation SQL: Structured Query Language

14 Appendices

14.1 Appendix A: Healthcare Analytics Glossary

Term	Definition
AMAM	Analytics Maturity Assessment Model - HIMSS standard for measuring healthcare analytics capabilities
Clinical Terminology	Standardized vocabularies including ICD-10, CPT, SNOMED, and RxNorm used in healthcare data
Conversational AI	Artificial intelligence systems that enable natural language interaction for complex tasks
EHR	Electronic Health Record - digital version of patient medical records
HIMSS	Healthcare Information and Management Systems Society - healthcare IT standards organization
Institutional Memory	Collective organizational knowledge, expertise, and practices that enable effectiveness

Term	Definition
NL2SQL	Natural Language to SQL - technology that converts spoken/written queries into database commands
Population Health	Analytics focused on health outcomes of groups of individuals rather than individual patients
RAG	Retrieval Augmented Generation - AI approach combining information retrieval with text generation

14.2 Appendix B: HIMSS Analytics Maturity Assessment Model (AMAM) Stages

Stage	Name	Description	Key Capabilities
Stage 0	Data Collection	Basic data capture without integration	Manual data entry, paper records
Stage 1	Data Verification	Automated data validation and error checking	Basic quality controls, automated checks
Stage 2	Data Utilization	Standard reporting and basic analytics	Automated reports, dashboard creation
Stage 3	Automated Decision Support	Rule-based clinical and operational support	Clinical alerts, automated protocols
Stage 4	Population Health Analytics	Population-level analysis and intervention	Cohort identification, risk stratification
Stage 5	Predictive Analytics	Statistical modeling and predictive capabilities	Predictive models, trend analysis
Stage 6	Cognitive Analytics	Machine learning and AI integration	Advanced AI, pattern recognition
Stage 7	Precision Medicine	Personalized treatment and genomic integration	Personalized care, genomic analytics

14.3 Appendix C: Healthcare NL2SQL Query Examples

14.3.1 Patient Population Analysis

Natural Language: “Show me all diabetic patients over 65 who had an HbA1c test in the last 6 months”

Generated SQL:

```
1 SELECT p.patient_id, p.age, l.test_date, l.result_value
2 FROM patients p
3 JOIN lab_results l ON p.patient_id = l.patient_id
4 JOIN diagnoses d ON p.patient_id = d.patient_id
5 WHERE d.icd10_code LIKE 'E11%' -- Type 2 Diabetes
6     AND p.age > 65
7     AND l.test_name = 'HbA1c'
8     AND l.test_date >= DATE_SUB(CURRENT_DATE, INTERVAL 6 MONTH)
```

14.3.2 Operational Metrics

Natural Language: “What is the average length of stay for cardiac surgery patients this year?”

Generated SQL:

```
1 SELECT AVG(DATEDIFF(discharge_date, admission_date)) as avg_los
2 FROM admissions a
3 JOIN procedures p ON a.admission_id = p.admission_id
4 WHERE p.cpt_code IN ('33510', '33511', '33512') -- Cardiac surgery codes
5     AND a.admission_date >= '2025-01-01'
6     AND a.discharge_date IS NOT NULL
```

14.3.3 Quality Metrics

Natural Language: “How many patients were readmitted within 30 days of discharge for heart failure?”

Generated SQL:

```
1 SELECT COUNT(DISTINCT r.patient_id) as readmission_count
2 FROM (
3     SELECT a1.patient_id, a1.discharge_date, a2.admission_date
4     FROM admissions a1
5     JOIN admissions a2 ON a1.patient_id = a2.patient_id
6     JOIN diagnoses d ON a2.admission_id = d.admission_id
7     WHERE d.icd10_code LIKE 'I50%' -- Heart failure
8         AND a2.admission_date BETWEEN a1.discharge_date AND DATE_ADD(a1.
9             discharge_date, INTERVAL 30 DAY)
10     AND a1.admission_id != a2.admission_id
11 ) r
```

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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/amaam/>
3. 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>
4. 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/pii/S0040162515003692>
5. 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>
6. 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>
7. Anthropic. Code modernization playbook: A practical guide to modernizing legacy systems with AI [Internet]. 2025. Available from: <https://resources.anthropic.com/code-modernization-playbook>

8. 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>
9. 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.almultidisciplinaryjournal.com/uploads/archives/20250306182550_MGE-2025-2-018.1.pdf
10. 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
11. Shen M K., Gandhi AD. Health care staff turnover and quality of care at nursing homes. JAMA Internal Medicine [Internet]. 2023;183(10):1088-95. Available from: <https://jamanetwork.com/journals/jamainternalmedicine/fullarticle/2809588>
12. 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>
13. Khan S S. Advanced business analytics in healthcare: Enhancing clinical decision support and operational efficiency. Business and Economics [Internet]. 2023; Available from: <https://publishing.emanresearch.org/index.php/bej/article/view/1136>
14. Lin L C. Barriers to physicians' adoption of healthcare information technology: An empirical study on multiple hospitals. Journal of Medical Systems [Internet]. 2012; Available from: <https://link.springer.com/article/10.1007/s10916-011-9656-7>
15. 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>

16. Richesson & K R. L. Data standards in clinical research: Gaps, overlaps, challenges and future directions. *Journal of the American Medical Informatics Association* [Internet]. 2007; Available from: <https://academic.oup.com/jamia/article/14/6/687/750453>
17. 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/>
18. Tyndall J. AACODS Checklist. Flinders University [Internet]. 2010. Available from: https://dspace.flinders.edu.au/jspui/bitstream/2328/3326/4/AACODS_Checklist.pdf
19. 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>
20. 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>
21. Wang H S. Capabilities of GPT-5 on multimodal medical reasoning. *arXiv preprint* [Internet]. 2025; Available from: <https://arxiv.org/abs/2508.08224>
22. OpenAI. HealthBench: A benchmark for evaluating LLMs in healthcare. *arXiv preprint* [Internet]. 2025; Available from: <https://arxiv.org/abs/2505.08775>
23. Jiang B Y., Chen J H. 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>
24. 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>
25. 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>

26. 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>
27. 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>
28. 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>
29. 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>
30. 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>
31. 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>
32. Dadi CB. 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; Available from: <https://al-kindipublishers.org/index.php/jcsts/article/view/8823>
33. 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>
34. 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>

35. Ipeirotis & Z. P. Natural Language Interfaces for Databases: What Do Users Think? arXiv preprint arXiv:2511.14718 [Internet]. 2025; Available from: <https://arxiv.org/abs/2511.14718>
36. 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>
37. 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>
38. 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/2019/2/e13331>
39. 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>
40. Saha G. B. K. NLINQ: A natural language interface for querying network performance. Applied Intelligence [Internet]. 2023; Available from: <https://link.springer.com/article/10.1007/s10489-023-04567-2>
41. Khandelwal A. P. 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>
42. 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>
43. 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>

44. 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>
45. 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>
46. 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>
47. 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>
48. 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>
49. 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>
50. 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>
51. 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>
52. 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>

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*. 2013.
55. Gökalp MO, Gökalp E, Gökalp S. The development of data analytics maturity assessment framework: DAMAF. *Journal of Software: Evolution and Process*. 2023;35(4):e2448.
56. Lismont J, Vanthienen J, Baesens B, et al. Defining analytics maturity indicators: A survey approach. *International Journal of Information Management*. 2017;37(3):114–24.
57. 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*. 2021;4(3):e211793.
58. 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*. 2002;9(6):600–11.
59. 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*. 2013;22(3):219–24.
60. 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.
61. Rahman P, Nandi A, Hebert C. Amplifying domain expertise in clinical data pipelines. *JMIR Medical Informatics*. 2020;8(11):e19612.
62. Sirgo G, Esteban F, Gómez J, 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*. 2018;112:166–72.

63. 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*. 2021;21:1-12.
64. 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*. 2016;2016.
65. 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). IEEE; 2017. p. 509-14.
66. Ulrich H, Kock-Schoppenhauer AK, et al. Understanding the nature of metadata: systematic review. *Journal of Medical Internet Research*. 2022;24(1):e25440.
67. 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*. 2017;17(1):1-10.
68. Hovenga EJ, Grain H. Health data and data governance. In: *Health information governance in a digital environment*. IOS Press; 2013. p. 67-94.
69. 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/>
70. 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>
71. Jones CB. The costs of nurse turnover, Part 2: Application of the nursing turnover cost calculation methodology. *Journal of Nursing Administration* [Internet]. 2005; Available from: https://journals.lww.com/jonajournal/abstract/2005/01000/the_costs_of_nurse_turnover_part_2_application.14.aspx
72. 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>

73. Melnick F E. R. Analysis of electronic health record use and clinical productivity and their association with physician turnover. JAMA Network Open [Internet]. 2021; Available from: <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2784810>
74. Oracle. The real cost of turnover in healthcare [Internet]. 2024. Available from: <https://www.oracle.com/human-capital-management/cost-employee-turnover-healthcare/>
75. 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>
76. 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/>
77. 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/>
78. 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>
79. 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>
80. Bae M S. H. Impact of nursing unit turnover on patient outcomes in hospitals. Journal of Nursing Scholarship [Internet]. 2010; Available from: <https://online.library.wiley.com/doi/abs/10.1111/j.1547-5069.2009.01319.x>

81. Wakerman H J. Remote health workforce turnover and retention: What are the policy and practice priorities? Human Resources for Health [Internet]. 2019; Available from: <https://human-resources-health.biomedcentral.com/articles/10.1186/s12960-019-0432-y>
82. Lahaie D. The impact of corporate memory loss: What happens when a senior executive leaves? Leadership in Health Services [Internet]. 2005; Available from: <https://www.emerald.com/insight/content/doi/10.1108/13660750510611198/full/html>
83. 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](https://www.redjournal.org/article/S0360-3016(16)00260-1/fulltext)
84. 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>
85. 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>
86. 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>
87. 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>
88. 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>
89. Milne-Ives DC M. The effectiveness of artificial intelligence conversational agents in health care: systematic review. Journal of Medical Internet Research [Internet]. 2020; Available from: <https://www.jmir.org/2020/10/e20346/>

90. Li L Y. Feasibility and effectiveness of artificial intelligence-driven conversational agents in healthcare interventions: A systematic review of randomized controlled trials. *International Journal of Medical Informatics* [Internet]. 2023; Available from: <https://www.sciencedirect.com/science/article/pii/S1386505623001296>
91. Rollwage H M. Using conversational AI to facilitate mental health assessments and improve clinical efficiency within psychotherapy services: real-world observational study. *JMIR AI* [Internet]. 2023; Available from: <https://ai.jmir.org/2023/1/e44358>
92. 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>
93. 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>
94. Dai & A T. Incorporating artificial intelligence into healthcare workflows: Models and insights. In. *Tutorials in Operations Research: Advancing the Frontiers of OR/MS* [Internet]. 2023; Available from: <https://pubsonline.informs.org/doi/abs/10.1287/educ.2023.0257>
95. Trust BHN. Empowering citizen developers: Low-code success in healthcare [Internet]. 2024. Available from: <https://ia.berkshirehealthcare.nhs.uk/citizen-developer-programme>
96. 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/>
97. 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>

98. Research F. The total economic impact of Microsoft Power Apps. Forrester Consulting [Internet]. 2024. Available from: <https://tef.forrester.com/go/microsoft/powerappstei/?lang=en-us>
99. 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
100. 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>
101. 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/>
102. 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>
103. Tan T J. P. Y. mHealth app to facilitate remote care for patients with COVID-19: rapid development of the DrCovid+ app. JMIR Formative Research [Internet]. 2023; Available from: <https://formative.jmir.org/2023/1/e38555>
104. Research P. Healthcare analytics market size and forecast 2025 to 2034 [Internet]. 2024. Available from: <https://www.precedenceresearch.com/healthcare-analytics-market>
105. 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>
106. 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>

107. Gal & R M. S. Data standardization. New York University Law Review [Internet]. 2019; Available from: <https://www.nyulawreview.org/issues/volume-94-number-4/data-standardization/>
108. Zheng R K. Studying workflow and workarounds in electronic health record-supported work to improve health system performance. Annals of Internal Medicine [Internet]. 2020; Available from: <https://www.acpjournals.org/doi/10.7326/M19-0871>
109. Bogaert V P. Identifying common enablers and barriers in European health information systems. Health Policy [Internet]. 2021; Available from: <https://www.sciencedirect.com/science/article/pii/S0168851021002396>
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 health-care, 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](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>