INTERNATIONAL MULTI DISCIPLINARY JOURNAL FOR RESEARCH & DEVELOPMENT
eISSN 2394-6334 Impact factor: 7,854 Volume 12, issue 11 (2025)

Architectures of Maintainability: Code Smells, Database Antipatterns, and Performance Trade-offs in Relational and Multi-Model Systems

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Abstract:
Background: Software maintainability remains a central challenge for long-lived information systems. Both application code and the databases they depend on contribute to ongoing maintenance costs; code smells and database antipatterns propagate technical debt and interact with performance tuning choices, creating complex trade-offs for engineering teams (Sharma & Spinellis, 2018; Karwin, 2010).

Objective: This research article integrates perspectives from empirical surveys, practitioner-oriented books, and recent database systems literature to generate a coherent theoretical framework that links maintainability predictors, code smells, SQL antipatterns, and performance optimization strategies for relational and emerging multi-model systems (Riaz et al., 2011; Yamashita & Moonen, 2013; Guo et al., 2024). Methods: We apply a structured analytical synthesis of the provided literature to (1) identify recurring predictors of maintainability, (2) classify how code smells and SQL antipatterns manifest in database-centric applications, and (3) elaborate how performance choices (fillfactor, HOT, sharding, indexing, query language expressiveness) alter maintainability and technical debt. The method relies on critical cross-referencing of empirical survey data, systematic taxonomies, and performance guidance to build propositions describing causal and moderating relationships among these concepts (Riaz et al., 2011; Sharma & Spinellis, 2018; PostgreSQL Global Development Group, 2023).

Results: The synthesis produces a detailed taxonomy mapping maintainability predictors to specific smells and antipatterns, demonstrates how modern PostgreSQL tuning parameters and NewSQL approaches present both opportunities and maintainability risks, and articulates design patterns to mitigate trade-offs. Key outcomes include: (a) a four-axis model of maintainability—comprehensibility, modifiability, testability, and operational resilience—each linked to concrete code and schema smells; (b) a decision matrix explaining when to prioritize performance optimizations (e.g., aggressive HOT optimization, sharding) and when to prioritize maintainability; and (c) a set of practitioner-oriented heuristics that reconcile Clean Code principles with database performance engineering (Martin, 2009; Karwin, 2010; PostgreSQL Global Development Group, 2023).

Conclusions: Maintainability in database-driven systems must be addressed holistically. Engineering teams benefit from formalizing maintainability predictors in their architectural reviews, applying smell-aware refactorings, and adopting performance practices that are reversible and well-documented. Future empirical work should validate the proposed model in controlled field studies across relational and multi-model deployments (Lu & Holubova, 2019; Guo et al., 2024).

Keywords: Maintainability, Code Smells, SQL Antipatterns, PostgreSQL Optimization, Multi-Model Databases, Technical Debt

INTRODUCTION

Software systems are socio-technical artifacts that evolve far beyond their initial release. Over the lifetime of an application, the cost of change often dwarfs the original development expense; maintainability therefore becomes a primary determinant of long-term viability and total cost of ownership (Riaz et al., 2011).

Systems that are database-driven face a confluence of sources that affect maintainability: the application source code, the database schema and queries, and operational-level performance optimizations. Each of these layers contains both design choices and emergent properties (smells, antipatterns, tuning parameters) that compound and interact, producing complex effects on comprehensibility, modifiability, and operational resilience (Sharma & Spinellis, 2018; Karwin, 2010).

Past research and practitioner literature approach these concerns from different vantage points. Empirical surveys of maintainability predictors highlight practitioner perceptions of what matters in software evolution; code smell literature catalogs recurring poor practices that foreshadow increased maintenance cost; database-oriented works enumerate SQL antipatterns and provide guidelines for performance tuning (Riaz et al., 2011; Yamashita & Moonen, 2013; Karwin, 2010; Martin, 2009). Meanwhile, the rapid expansion of data models and systems—multi-model databases, NewSQL, sharded RDBMS options—introduces new axes along which maintainability and performance trade-offs must be considered (Lu & Holubova, 2019; Guo et al., 2024; Krishnappa et al., 2024).

This work seeks to synthesize these perspectives in a single, theoretically coherent article that advances understanding of how maintainability predictors map to concrete smells and antipatterns in database-driven applications and how performance optimization choices influence long-term maintainability. The goal is not to present new empirical data collected by the author; rather, through rigorous analytical synthesis of extant literature provided in the input references, the article constructs a conceptual model and practical heuristics that are directly actionable for researchers and practitioners. By doing so, this article addresses a clear gap: while prior works examine code smells and database antipatterns individually and while performance guides provide tuning advice, there is limited integrated theorization of how these domains interact to affect maintainability across architectural decisions and runtime tuning.

The problem statement is thus: how can engineering teams reason about, measure, and mitigate maintainability risks in database-dependent systems while still achieving necessary performance targets? In answering this, the article pursues three objectives. First, to collect and synthesize maintainability predictors and map them to code and schema level symptoms identified in the literature (Riaz et al., 2011; Yamashita & Moonen, 2013; Sharma & Spinellis, 2018). Second, to explicate how database performance choices—including PostgreSQL-specific tuning practices, sharding strategies, and multi-model considerations—interact with maintainability (PostgreSQL Global Development Group, 2023; Krishnappa et al., 2024). Third, to propose a set of design heuristics and governance practices that balance performance and maintainability, with explicit attention to reversibility and documentation (Martin, 2009; Karwin, 2010).

The rest of the article is organized to elaborate these aims. The methodology section explains the analytic synthesis approach, describing how evidence from the referenced works is triangulated to produce propositions and a taxonomy. The results present the taxonomy and derived decision frameworks. The discussion interprets these results, explores limitations, and outlines future research directions. The conclusion consolidates practical recommendations for teams striving to maintain code and database quality while meeting performance needs.

METHODOLOGY

This article adopts a structured analytical synthesis methodology that treats the provided references as the empirical and conceptual basis for theoretical development. Instead of performing new empirical measurement, the method systematically extracts, cross-references, and integrates findings, taxonomies, and practitioner guidance from the corpus to build a coherent model. The rationale for this approach is twofold: (1) the supplied literature contains complementary empirical surveys, systematic taxonomies, and

performance documentation that, when integrated, yield more comprehensive insights than any single source; (2) theory building through rigorous synthesis is an established method in software engineering when primary data collection is not practical or when the objective is to generate testable propositions for later empirical validation.

The procedure followed these steps:

Source Identification and Characterization. Each reference was examined for its primary contribution: empirical survey data (Riaz et al., 2011; Yamashita & Moonen, 2013), smell and antipattern taxonomies (Sharma & Spinellis, 2018; Karwin, 2010), practitioner guidance on coding and architecture (Martin, 2009), and system-level performance documentation and research on database architectures (PostgreSQL Global Development Group, 2023; Guo et al., 2024; Lu & Holubova, 2019; Krishnappa et al., 2024). This step catalogued the focal constructs, definitions, and measurement approaches present in each work.

Construct Mapping. Fundamental constructs were identified and mapped across sources. These include maintainability predictors (e.g., modularity, documentation, test coverage), code smells (e.g., duplicated code, long methods, feature envy), SQL antipatterns (e.g., SELECT N+1, improper normalization), and performance tuning elements (e.g., fillfactor, HOT percentages, shard distribution). Mapping focused on aligning terms (for example, recognizing how "comprehensibility" in a maintainability survey corresponds to "readability" in code smell literature and to "schema clarity" in database literature).

Evidence Integration. For each mapped construct, assertions or propositions were derived that reflect the consensus or debate in the literature. Wherever a literature source provided explicit empirical evidence (e.g., survey results on which factors practitioners believe affect maintainability), that evidence was used as the primary anchor (Riaz et al., 2011; Yamashita & Moonen, 2013). For practitioner guidance (Martin, 2009; Karwin, 2010), prescriptions were treated as normative statements and used to relate code and database design decisions to maintainability outcomes.

Model Construction. Using the integrated evidence, a four-axis model of maintainability was developed—comprehensibility, modifiability, testability, and operational resilience—intended to be broad yet specific enough to link to concrete smells and antipatterns. For each axis, causal pathways were elaborated showing how particular code smells and SQL antipatterns lead to diminished maintainability, and how specific performance optimizations either exacerbate or mitigate those effects.

Decision Framework. A performance-vs-maintainability decision matrix was created by synthesizing guidance from PostgreSQL documentation and performance literature (PostgreSQL Global Development Group, 2023; Ferguson, 2021; Finkel, 2022) and from multi-model and NewSQL literature that discuss distribution, expressiveness, and scalability trade-offs (Guo et al., 2024; Lu & Holubova, 2019; Krishnappa et al., 2024). The decision framework enumerates conditions under which performance optimizations (like sharding, specialized indexing, or fillfactor tuning) are justified, and prescribes steps to preserve maintainability (e.g., encapsulation of database access, documentation, feature flags).

Analytic Rigor and Citation Discipline. A core methodological requirement was that every major claim be traceable to at least one cited source among the references provided. Empirical claims were explicitly tied to empirical sources; prescriptive claims were tied to practitioner texts or documentation. Where synthesis involved inference beyond a single source, the contributing sources were cited together to make transparent the evidentiary basis.

Limitations of the Method. Because the synthesis relies solely on provided references and does not introduce

new empirical data, claims are theoretical and should be validated in subsequent empirical studies. Nevertheless, the methodology prioritizes fidelity to the primary sources and aims to produce testable propositions and practical heuristics grounded in established work (Riaz et al., 2011; Sharma & Spinellis, 2018; Karwin, 2010; Martin, 2009).

RESULTS

The synthesis yields three interrelated results: (1) a taxonomy mapping maintainability predictors to specific code smells and SQL antipatterns; (2) a model of how performance optimizations interact with maintainability across common engineering practices; and (3) a set of practical heuristics—actionable, reversible steps for teams to follow when balancing performance and maintainability.

Taxonomy: Maintainability Predictors Mapped to Smells and Antipatterns

The literature identifies core predictors that practitioners associate with maintainability: modularity and separation of concerns, documentation and naming, test coverage and automated testing, code size and complexity, and database schema clarity and normalization (Riaz et al., 2011; Yamashita & Moonen, 2013). Sharma and Spinellis (2018) systematically catalog code smells, showing how these symptoms map onto maintainability outcomes. Karwin (2010) details SQL antipatterns that often directly degrade schema clarity and query maintainability. Combining these sources produces a detailed mapping, summarized below in descriptive form.

Comprehensibility. Comprehensibility captures how easily a maintainer can form an accurate mental model of the system. It is harmed by code smells such as duplicated code, long methods, and cryptic naming, and by SQL antipatterns such as "ambiguous column naming," deeply nested queries without comments, and overuse of ad-hoc denormalized structures (Sharma & Spinellis, 2018; Karwin, 2010). The literature emphasizes that developers' ability to reason about code and queries directly affects how quickly and accurately faults are diagnosed (Yamashita & Moonen, 2013).

Modifiability. Modifiability is the capacity to implement changes with minimal unintended consequences. It is eroded by tight coupling, feature envy (methods too reliant on external objects), and database antipatterns like direct manipulation of application logic within triggers or stored procedures that are insufficiently modularized (Martin, 2009; Karwin, 2010). Riaz et al. (2011) identify modularity and clear separation of concerns as key maintainability predictors—corroborating that modifiability is an engineering attribute highly sensitive to architecture.

Testability. Testability depends on the ease of isolating components and verifying behavior. Code smells such as large classes and hidden dependencies reduce testability, as do database practices that hinder deterministic testing—such as reliance on non-idempotent stored procedures, environmental state embedded in queries, or heavy reliance on database configuration tuned for production without controlled test settings (Riaz et al., 2011; Martin, 2009). Yamashita and Moonen (2013) show in survey data that developers value testability and often attribute the presence of smells to decreased test quality.

Operational Resilience. Operational resilience refers to systems' behavior under load and during live modifications (e.g., schema migrations). Antipatterns like using large monolithic migrations, neglecting indices, or employing sharding without consistent routing logic increase the risk of outages during maintenance. Performance tuning practices—like aggressive fillfactor changes or HOT optimization in PostgreSQL to reduce page splits—can improve latency but, if undocumented or non-reversible, decrease operational resilience by making the system stateful in non-transparent ways (PostgreSQL Global

Development Group, 2023; Natti, 2023). The literature confirms that operations and maintainability are intertwined; decisions intended to optimize runtime can have persistent effects on how maintainers reason about, and modify, systems.

Model: Interaction Between Performance Optimizations and Maintainability

Performance optimizations act through multiple mechanisms: they change the runtime characteristics of queries and storage, introduce additional layers of configuration and code (e.g., shard routing libraries), and sometimes require schema-level denormalization or the use of specialized indexes. The results show three archetypal interaction patterns.

Preservative Optimizations. These are optimizations that improve performance without undermining maintainability when applied conservatively and accompanied by documentation and encapsulation. Examples include creating appropriate indices with clear naming conventions, annotating complex queries, and applying fillfactor adjustments to high-update tables with documented rationale. PostgreSQL documentation and practitioner books emphasize that careful tuning—combined with test workloads and rollback plans—can preserve maintainability (PostgreSQL Global Development Group, 2023; Ferguson, 2021).

Transformative Optimizations. Transformative optimizations fundamentally alter the architecture, requiring explicit design commitments that affect maintainability. Sharding (Krishnappa et al., 2024) and moving to NewSQL or multi-model systems (Lu & Holubova, 2019; Guo et al., 2024) are transformative: they may be necessary for scale but introduce cross-cutting complexity—routing logic, eventual consistency semantics, and heterogeneous query languages—that increases cognitive load for maintainers and requires new testing and deployment strategies.

Opaque Optimizations. Opaque optimizations are low-level tuning actions that, if undocumented, create hidden dependencies and therefore reduce maintainability. Examples include ad hoc index creation based on one workload that later proves harmful, extensive trigger usage to get application semantics into the database, undocumented fillfactor and HOT adjustments (Natti, 2023), or manual partitioning with bespoke routing code. The PostgreSQL documentation warns that such optimizations must be carefully controlled; otherwise, they produce operational surprises (PostgreSQL Global Development Group, 2023).

Decision Matrix: Balancing Performance and Maintainability

From the model, the synthesis derives a decision matrix that guides when to prioritize which concerns. The matrix evaluates four dimensions: workload characteristics (read vs. write heavy, latency requirements), team expertise (database and distributed systems competence), criticality of uptime (SLAs, risk tolerance), and pace of functional change (fast evolving vs. stable features). The matrix prescribes:

When to Prioritize Maintainability. If the pace of functional change is high and the team has modest database expertise, favor conservative designs: normalized schemas, attention to clean code in data access layers, minimal use of database-specific stored logic, and generic indexing strategies (Riaz et al., 2011; Martin, 2009; Karwin, 2010).

When to Prioritize Performance (with Controls). If workloads are latency sensitive or data volume mandates distribution, prefer transformative solutions but accompany them with strong governance: encapsulate data access through well-documented APIs, version database schema changes, use reversible deployment strategies (feature flags, blue/green migrations), and ensure extensive automated testing, including realistic

load tests (Krishnappa et al., 2024; Guo et al., 2024).

When to Apply Preservative Optimizations. For many systems, incremental tuning—indexing, fillfactor adjustments, HOT tuning, partitioning—delivers significant gains. Such measures should be performed with clear rollback plans, test harnesses, and documentation that expresses the motivation and expected lifetime of the optimization (PostgreSQL Global Development Group, 2023; Natti, 2023).

Heuristics: Operational and Code Governance Practices

The literature supports a set of heuristics to operationalize the matrix. These include: (1) maintain an explicit "database design rationale" alongside code documentation (Martin, 2009; Karwin, 2010); (2) modularize database access through a thin data access layer so that physical schema changes are isolated from broader business logic (Riaz et al., 2011); (3) prefer query expressiveness that is portable and documented, particularly when considering multi-model or NewSQL approaches (Ong et al., 2015; Guo et al., 2024); (4) codify performance optimizations as migration scripts with explicit test cases and rollback instructions (PostgreSQL Global Development Group, 2023; Ferguson, 2021); and (5) treat smells as early warning signals and apply refactorings systematically rather than ad hoc (Sharma & Spinellis, 2018; Yamashita & Moonen, 2013).

DISCUSSION

The synthesis presented in the results section yields a rich and actionable conceptual framework, but it also invites careful interpretation regarding its implications and limitations, and it suggests concrete future research pathways.

Interpretation: Why Integrated Thinking Matters

The central insight is that maintainability cannot be meaningfully improved by focusing only on source code or only on database schema; the two are interdependent. Empirical surveys show that practitioners attribute maintainability outcomes to factors ranging from coding standards to documentation and testing infrastructure (Riaz et al., 2011; Yamashita & Moonen, 2013). Code smells commonly cited in the literature (Sharma & Spinellis, 2018) are not mere stylistic issues; they degrade testability and error proneness in ways that cascade into database evolution. For example, duplicated logic in application code often coexists with database triggers that attempt to enforce the same invariants; this duplication increases the probability of inconsistent changes and complicates migration activities (Karwin, 2010).

Furthermore, performance tuning decisions influence maintainability both positively and negatively. When done transparently and reversibly (preservative optimizations), they can be a net gain: lower latency improves the operational behavior and may reduce emergency work. Conversely, opaque optimizations create technical debt: undocumented fillfactor changes, for instance, might reduce page bloat but, if not tracked, lead future maintainers to misinterpret performance anomalies as logic bugs rather than tuning artifacts (PostgreSQL Global Development Group, 2023; Natti, 2023). This points to a governance problem as much as a technical problem.

Reconciling Clean Code with Performance Needs

Martin's Clean Code ethos (Martin, 2009) emphasizes clarity, small functions, and explicit separation of concerns—principles that appear at odds with some performance suggestions (e.g., denormalization for read performance). The synthesis suggests that the apparent conflict is resolvable by focusing on reversibility and

encapsulation. Denormalization can be acceptable if the denormalized representation is treated as a derived view with clear generation and refresh mechanics, exposed through well-documented interfaces. Similarly, stored procedures and triggers—traditionally discouraged in a purely application logic viewpoint—can be leveraged when their responsibilities are narrow, documented, and covered by tests (Karwin, 2010).

The literature on multi-model databases complicates these considerations further. Multi-model systems promise flexibility in handling a variety of data shapes and access patterns (Lu & Holubova, 2019; Guo et al., 2024). They may reduce the need for awkward denormalization in relational databases by allowing documents, graphs, and relational tables to coexist. But this expressiveness comes at the cost of new operational and cognitive complexity: different query languages or dialects, diverse indexing strategies, and more sophisticated consistency models. Thus, migrating to multi-model approaches should be understood as a transformative optimization requiring higher team capability and stronger governance (Guo et al., 2024).

Limitations and Threats to Validity

Given that this work synthesizes provided literature rather than contributing new empirical data, it has inherent limitations. First, the propositions and the decision matrix require empirical validation. The survey evidence used (Riaz et al., 2011; Yamashita & Moonen, 2013) reflects developers' perceptions; while such perceptions are important, they are not equivalent to causal proof. Second, the practitioner books and documentation (Martin, 2009; Karwin, 2010; PostgreSQL Global Development Group, 2023) provide normative guidance that may vary in practicality across teams with different constraints. Third, the references related to modern database architectures (Guo et al., 2024; Lu & Holubova, 2019; Krishnappa et al., 2024) introduce fast-moving topics—sharding, NewSQL, and multi-model features—that may outpace the static synthesis here; their operational implications will differ across product contexts.

To partially mitigate concerns about over-generalization, the synthesis deliberately classifies optimizations and design choices into archetypes (preservative, transformative, opaque), enabling practitioners to make contextual assessments rather than applying one-size-fits-all rules. Nevertheless, future empirical research should test the model in diverse settings—startups, legacy enterprise systems, high-throughput services—to measure how strongly particular smells and antipatterns predict maintainability outcomes and to quantify the maintainability cost of specific performance interventions.

Future Research Directions

The synthesis points to several fruitful empirical pathways. A longitudinal field study could instrument teams as they adopt performance optimizations (e.g., moving to sharding, applying fillfactor tuning, denormalizing views) and track maintainability metrics over time (e.g., mean time to repair, change lead time, test coverage evolution). Such a study would make it possible to measure the causal impact of performance optimizations on maintainability and to identify mediating factors (e.g., documentation practices, test harnesses).

Another empirical approach would be controlled experiments in which development teams are given tasks requiring schema change under different constraints (with or without performance optimizations and with varying levels of smell density in the starting codebase). Outcome measures could quantify change difficulty and fault introduction rates, thereby testing the synthesized taxonomy's predictive power.

Additionally, research should investigate tool support for managing the intersection of code smells and database antipatterns. For instance, static analysis tools are mature for code smells; extending them to analyze SQL embedded in code and to detect dangerous database configuration drift (undocumented

fillfactor changes, ad hoc indexes) could be highly valuable. Integrating such analysis into continuous integration pipelines could operationalize the heuristics proposed here and keep the system in a "preservative optimization" posture rather than degenerating into "opaque optimization."

Practical Recommendations for Teams

Based on the integrated evidence, the following recommendations are concise, actionable, and directly tied to the literature:

1. Maintain a "database design rationale" document alongside code comments and commits, tracking the motivation for schema choices and performance optimizations (Martin, 2009; Karwin, 2010).

2. Encapsulate database access behind a thin data access layer to localize schema impacts and make refactorings safer (Riaz et al., 2011).

3. Treat performance optimizations as migrations: codify them in scripts, include test plans that replicate the workload, and provide rollback procedures (PostgreSQL Global Development Group, 2023; Ferguson, 2021).

4. Use smells as triggers for scheduled refactoring rather than ad hoc edits. Prioritize smell removal when it aligns with upcoming feature changes to amortize refactoring cost (Sharma & Spinellis, 2018; Yamashita & Moonen, 2013).

5. When contemplating multi-model or NewSQL adoption, evaluate team capability and governance readiness; such transitions are transformative and demand investment in new test and deployment patterns (Lu & Holubova, 2019; Guo et al., 2024; Krishnappa et al., 2024).

CONCLUSION

This article synthesizes insights from empirical surveys, code smell taxonomies, SQL antipattern guides, and performance documentation to produce an integrated framework for understanding and managing maintainability in database-driven systems. The core contribution is a taxonomy that links maintainability predictors to code smells and SQL antipatterns, a model of how performance optimizations interact with maintainability (preservative, transformative, opaque), and a decision matrix and heuristics that guide practitioners in balancing performance and maintainability.

The evidence suggests that maintainability improves most when teams treat performance optimizations as first-class engineering artifacts: documented, reversible, and tested. Clean Code principles remain a powerful compass, but they must be reconciled with pragmatic database engineering. Multi-model and NewSQL platforms expand expressive power and scalability but introduce new complexity that must be managed with governance and capability building.

Finally, while the synthesis is grounded in the referenced literature, the propositions and prescriptions must be empirically validated. The next step for the research community is to operationalize the taxonomy in instruments and to conduct longitudinal and experimental studies assessing the maintainability impact of specific smells and optimizations across diverse contexts. Until such validation is available, practitioners should adopt the heuristics proposed here as risk-aware guidelines rather than immutable rules.

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