International Journal of Artificial Intelligence, Data Science, and Machine Learning
Grace Horizon Publication | Volume 5, Issue 4, 345-356, 2024
ISSN: 3050-9262 | https://doi.org/10.63282/3050-9262.IJAIDSML-V5I4P130

Original Article

Retrieval-Augmented Software Engineering for Enterprise Codebases: Context-Aware Requirement Traceability, Bug Localization, and Developer Decision Support

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Abstract *- Enterprise software engineering increasingly operates under conditions of scale, regulatory exposure, architectural fragmentation, and accelerated delivery pressure. Large codebases are distributed across services, repositories, branches, build pipelines, requirements systems, incident records, design documents, and operational telemetry. In this setting, developers and engineering leaders must answer high-stakes questions: which code implements a requirement, where a defect is likely to be fixed, which architectural dependency explains a failure, and what decision is justified by available engineering evidence. This paper proposes RASE, a retrieval-augmented software engineering framework for context-aware requirement traceability, bug localization, and developer decision support in enterprise codebases. RASE treats software engineering artifacts as a governed, typed, versioned, and auditable knowledge substrate rather than a passive document collection. The framework combines hybrid lexical–dense retrieval, code-aware embeddings, dependency graphs, evidence ranking, retrieval-conditioned generation, and decision governance. Unlike generic retrieval-augmented generation pipelines, RASE introduces artifact-type aware chunking, traceability-preserving metadata, multi-hop retrieval over code and non-code artifacts, and evidence contracts that constrain generated recommendations to retrieved, inspectable sources. The paper presents a research design, architecture, operational workflow, and reproducible evaluation protocol for three core tasks: recovering requirement-to-code links, localizing buggy files from reports and incidents, and supporting developer decisions during design, change impact analysis, and release governance. The proposed evaluation emphasizes recall-oriented retrieval quality, developer-facing usefulness, provenance precision, latency, security, and organizational adoption. The contribution is a research-grade framework that integrates established information retrieval principles, modern code representation learning, secure software development governance, and AI-enabled lifecycle management into a unified enterprise software engineering method. RASE is positioned as an empirical artifact for future controlled industrial validation, with clearly defined research questions, hypotheses, metrics, ablation strategy, and threats to validity.*

Keywords *- Retrieval-Augmented Generation, Software Engineering, Requirement Traceability, Bug Localization, Enterprise Codebases, Code Intelligence, Developer Decision Support, Software Governance, Hybrid Retrieval, Explainable AI.*

1. Introduction

Enterprise codebases are not merely large collections of source files. They are socio-technical systems composed of requirements, code, tests, build scripts, service contracts, architecture diagrams, database schemas, observability records, incident reports, security controls, and release decisions. The practical difficulty is that critical engineering knowledge is distributed across tools and often changes faster than documentation can be maintained. Requirements are refined in work-tracking systems, implementation details are dispersed across repositories, defects are discussed in tickets and chat logs, and operational failure evidence appears in metrics, traces, logs, and alerts. As a result, developers frequently rely on partial memory, informal ownership knowledge, keyword search, and manual code reading. Retrieval-augmented generation provides a promising foundation because it combines parametric model reasoning with explicit non-parametric evidence retrieved from an external corpus [1].

However, enterprise software engineering differs from open-domain question answering. A retrieved paragraph from a document is not enough to justify a code change. A developer needs traceable evidence across artifact types: a requirement, a design decision, relevant source files, tests, historical commits, similar defects, dependency paths, deployment records, and security policies. The retrieval problem is therefore contextual, multi-hop, temporal, and governed. It must respect repository versioning, access control, regulated information boundaries, and the difference between semantic similarity and engineering relevance. Classical software traceability research already recognized that information retrieval can recover links between code

and documentation, but enterprise-scale AI systems require this idea to be extended into a continuously updated, evidence-aware decision layer [3].

The motivation for this paper is the gap between generic AI coding assistants and enterprise-grade software engineering support. Coding assistants can generate snippets or answer isolated questions, but enterprises require systems that can justify recommendations, explain uncertainty, preserve provenance, and integrate with lifecycle governance. AI-driven lifecycle governance research has emphasized the importance of decision intelligence, defect prediction, testing automation, and architecture-centered project management, which aligns with the need for a unified retrieval substrate across engineering workflows [32]. Yet those capabilities are often deployed as separate tools rather than as a common retrieval-augmented architecture.

This paper proposes RASE, a retrieval-augmented software engineering framework for enterprise codebases. RASE is designed for three tasks that are both high-value and evidence-intensive. First, it supports context-aware requirement traceability by recovering, ranking, and explaining links among requirements, design elements, source files, APIs, database entities, tests, and deployment controls. Second, it supports bug localization by combining bug report text, stack traces, logs, similar historical defects, code embeddings, dependency graphs, and ownership metadata. Third, it supports developer decision-making by grounding recommendations in retrieved evidence and producing auditable decision cards. These tasks are selected because they represent recurring enterprise pain points, have measurable retrieval and human evaluation metrics, and connect directly to software governance outcomes.

The paper is framed as design-science research. The research artifact is not a generic chatbot, but an architecture, data model, retrieval method, and evaluation protocol for enterprise software engineering. The central claim is that retrieval-augmented software engineering becomes enterprise-grade only when retrieval is artifact-aware, context-aware, provenance-preserving, security-constrained, and decision-oriented. This claim builds on traceability research, modern code models, defect prediction work, cloud observability, and secure development guidance. For example, service dependency modeling has shown that graph-based representations are valuable for predicting failure propagation in distributed systems [10]. RASE generalizes that insight by treating dependency graphs as first-class retrieval structures rather than as separate observability artifacts.

The contribution of this paper is fourfold. First, it defines a unified artifact graph for enterprise software engineering, including requirements, code, tests, incidents, commits, services, dependencies, and governance controls. Second, it proposes a hybrid retrieval method that combines BM25-style lexical retrieval, dense code-document retrieval, graph expansion, and cross-encoder reranking. Third, it defines retrieval-conditioned decision support outputs that explicitly separate evidence, inference, uncertainty, recommended action, and validation step. Fourth, it presents a reproducible evaluation protocol that can be applied to open-source benchmark repositories, anonymized enterprise repositories, or mixed industrial datasets without requiring the invention of unsupported empirical results.

2. Research Problem, Objectives, and Questions

The research problem addressed in this paper is: How can retrieval-augmented methods be designed for enterprise software engineering so that they improve requirement traceability, bug localization, and developer decision support while preserving provenance, security, and governance? The problem is difficult because enterprise codebases contain heterogeneous artifacts with different structures, temporal properties, and trust levels. A requirement may be written in natural language, a code file may express behavior through control and data flow, a test may encode implicit acceptance criteria, and an incident ticket may contain noisy operational symptoms. A retrieval system must connect these artifacts without collapsing them into undifferentiated text chunks.

The first objective is to define a representation layer that makes software artifacts retrievable without losing engineering semantics. Naive chunking can break a method away from its class, a log message away from its service, or a test assertion away from its requirement. RASE therefore introduces artifact-aware chunking units such as requirement clauses, class-level summaries, method bodies, API endpoint records, test cases, configuration blocks, commit messages, incident sections, and architecture decision records. Each unit is associated with typed metadata, including repository, branch, service, owner, timestamp, artifact type, security classification, and dependency relations. This is consistent with enterprise microservice and cloud-native design concerns, where reliable software operation depends on architecture-level context as much as on individual source files [4].

The second objective is to design retrieval as a staged process rather than as a single nearest-neighbor query. Enterprise questions often begin vague and become answerable only after context expansion. For example, a bug report stating that “card authorization intermittently fails after timeout recovery” may require retrieval of logs, payment-service handlers, retry policies, configuration files, previous incidents, test gaps, and recent commits. Dense retrieval methods can identify semantically related artifacts, but lexical retrieval remains important for identifiers, error codes, API names, stack trace symbols, and database

fields. RASE therefore uses hybrid retrieval grounded in probabilistic lexical ranking and modern embedding-based retrieval [7].

The third objective is to preserve evidence quality. Retrieval-augmented generation can produce plausible but unsupported explanations if the generative model is not constrained by retrieved evidence. RASE addresses this through evidence contracts. An evidence contract requires that each recommendation identify the retrieved artifacts that support it, indicate whether the support is direct or inferred, state confidence limitations, and specify validation actions such as test execution, code review, or log inspection. This design is influenced by explainable and auditable decision pathway requirements in regulated fraud detection systems, where decision outputs must be inspectable rather than merely predictive [14].

The fourth objective is to support research evaluation. The proposed framework is evaluated through task-level metrics and human-centered software engineering measures. Requirement traceability can be measured using precision, recall, mean average precision, and analyst effort reduction. Bug localization can be measured using mean reciprocal rank, top-k accuracy, effort-aware ranking, and developer validation. Decision support can be evaluated through correctness, usefulness, evidence sufficiency, actionability, and time-to-resolution. Secure software governance can be evaluated using access compliance, provenance completeness, auditability, and leakage prevention aligned with secure development principles [27].

The paper is guided by three research questions. RQ1: How can artifact-aware hybrid retrieval improve requirement-to-code and requirement-to-test traceability in enterprise repositories? RQ2: How can retrieval over bug reports, code, commits, logs, and dependency graphs improve bug localization compared with single-source retrieval baselines? RQ3: How can retrieval-conditioned evidence contracts improve developer decision support while reducing unsupported recommendations? These questions make the paper empirical in orientation even though this manuscript does not fabricate numerical results. Instead, it provides a concrete research artifact and a protocol for future validation in open-source or industrial settings.

3. Foundations and Related Research

The intellectual foundation of RASE begins with software traceability. Traceability links connect requirements to downstream artifacts such as design elements, source code, tests, and maintenance records. Early information retrieval approaches demonstrated that textual similarity could recover links between source code and documentation, establishing a core idea that software artifacts can be treated as retrievable evidence [3]. Latent semantic indexing further showed that vocabulary mismatch between documentation and code could be mitigated by lower-dimensional semantic representations, which is directly relevant to modern dense retrieval [11]. These early methods remain important because enterprise software still contains identifiers, comments, ticket titles, and domain vocabulary that lexical and statistical models can exploit.

Modern traceability research has also emphasized that trace links are not merely search results. They support impact analysis, compliance, maintenance, safety assurance, and project memory. Future-oriented traceability work has highlighted the need for scalable, adaptive, and developer-integrated traceability mechanisms in complex engineering environments [29]. RASE extends this direction by incorporating retrieval-augmented decision support and graph-based context expansion. Instead of treating traceability recovery as a periodic offline task, RASE treats it as a continuous service that can answer developer questions, update links after changes, and expose uncertainty when evidence is incomplete.

Bug localization research provides the second foundation. Information retrieval-based bug localization ranks source files according to their likelihood of containing the fault described by a bug report. BugLocator demonstrated that bug reports and source files can be connected through revised vector space modeling and historical bug similarity [13]. Later structured retrieval approaches incorporated file names, package names, comments, and code structure, improving localization by respecting the structure of software artifacts [21]. These methods are especially relevant to RASE because enterprise defect reports often include noisy natural language, stack traces, logs, and operational context. A retrieval-augmented system must combine these signals rather than rely on one representation.

The third foundation is code representation learning. Transformer-based architectures created a new basis for learning contextual representations of text and code [19]. CodeBERT introduced bimodal pretraining over programming language and natural language, supporting tasks such as code search and documentation generation [9]. GraphCodeBERT further incorporated data-flow structure, recognizing that code semantics are not fully captured by token sequences [5]. These models support the RASE design principle that code retrieval should preserve program structure when possible. For enterprise use, embedding models must also be complemented by repository metadata, dependency graphs, and lexical retrieval because business identifiers and proprietary naming conventions may not be well represented in general-purpose pretrained models.

The fourth foundation is retrieval-augmented generation itself. RAG combines a generative model with explicit retrieved evidence, enabling generated responses to use external memory and provide more factual, specific outputs than purely parametric generation [1]. Dense passage retrieval showed that learned dual encoders can retrieve relevant passages for question answering using vector similarity [23]. However, enterprise software engineering requires stronger constraints than

open-domain question answering. Retrieved items must include code, tests, logs, requirements, and historical decisions, and generated outputs must not overstate evidence. RASE adapts RAG from knowledge-intensive NLP into engineering-intensive decision support.

The fifth foundation is enterprise lifecycle intelligence. AI-driven lifecycle governance, ML-based defect prediction, and automated testing frameworks have been proposed to improve software quality and governance across agile delivery processes [2]. Predictive analytics and caching-based optimization in pharmacy inventory systems show how domain-specific operational intelligence can improve enterprise process performance when integrated with architecture and data flows [22]. Similarly, intelligent CI/CD risk detection for banking systems illustrates how machine learning can be embedded into real deployment governance rather than isolated offline prediction [20]. RASE builds on these ideas by positioning retrieval as the common evidence layer through which predictive, generative, and governance components interact.

Cloud observability and root cause analysis are also essential. Adaptive intelligence in cloud systems has emphasized AI-enhanced observability and automated root cause analysis as a unified architecture problem [28]. Enterprise bug localization increasingly depends on runtime evidence, especially in microservices where failures propagate across service boundaries. Graph-based dependency modeling can identify likely propagation paths and improve failure reasoning in distributed systems [10]. RASE incorporates dependency-aware retrieval so that incident evidence can expand from a failing endpoint to upstream callers, downstream dependencies, configuration changes, and recent deployment events.

Finally, secure and regulated software development provides governance constraints. Secure software development frameworks emphasize integrating security practices into the software lifecycle rather than treating them as after-the-fact controls [27]. Enterprise retrieval systems must therefore enforce access control, prevent sensitive data leakage, preserve audit logs, and support secure change decisions. Work on privacy-preserving federated fraud detection also shows that enterprise AI architectures may require distributed learning and governance protocols when data cannot be centralized [8]. RASE is designed to operate under these constraints by separating index partitions, enforcing policy-aware retrieval, and retaining provenance for audit.

4. Proposed Framework: RASE

RASE is organized into six layers: artifact ingestion, semantic normalization, hybrid indexing, context planning, evidence-constrained generation, and governance feedback. The architecture is designed to be implemented incrementally in enterprises that already use version control, issue tracking, CI/CD, observability platforms, and documentation systems. It does not require a single monolithic repository. Instead, it creates a governed retrieval plane across existing engineering systems.

The artifact ingestion layer collects software engineering artifacts from source repositories, issue trackers, test systems, documentation repositories, CI/CD pipelines, observability stores, and security scanners. Source artifacts include files, classes, methods, modules, configuration files, infrastructure-as-code templates, database migration scripts, and API specifications. Process artifacts include requirements, user stories, defects, incidents, commits, pull requests, code reviews, release notes, architecture decision records, and risk approvals. Runtime artifacts include logs, traces, metrics, alerts, exception records, and deployment events. Testing artifacts include unit tests, integration tests, regression suites, automated test reports, and flaky-test records. This broad ingestion scope is necessary because enterprise engineering questions rarely map to only one artifact type.

The semantic normalization layer converts raw artifacts into typed retrieval units. A requirement is decomposed into objective, constraint, acceptance criterion, affected capability, and compliance tag. A source file is decomposed into file summary, class summary, method-level chunks, imports, call relations, and comments. A test file is decomposed into test cases, assertions, fixtures, and coverage metadata. A bug report is decomposed into symptom, environment, expected behavior, observed behavior, stack trace, reproduction steps, and attachments. This layer also standardizes identifiers by linking service names, package names, API routes, database tables, configuration keys, and domain entities. The importance of testing structure is reinforced by comparative work on automated testing frameworks in Java enterprise systems, where test reliability depends on framework behavior, coverage, maintainability, and integration with development workflows [30].

The hybrid indexing layer maintains multiple indexes over the same artifact graph. A lexical index supports exact matching over identifiers, error codes, API names, file paths, and domain terms. A dense vector index supports semantic retrieval over requirements, code summaries, comments, bug descriptions, and architectural documentation. A graph index supports dependency expansion through call graphs, service dependencies, data-flow links, requirement hierarchies, and ownership relations. A temporal index supports retrieval by release, branch, incident window, deployment event, and commit history. For vector search, efficient similarity search methods are required because enterprise indexes may include millions of chunks across active and historical repositories [15].

The context planning layer interprets a developer query and constructs a retrieval plan. A query such as “Does the new loan prepayment rule affect amortization tests?” is classified as a traceability and impact-analysis task. The planner retrieves

requirement clauses, affected domain terms, code modules, tests, recent commits, and architecture records. A query such as "Where should this NullPointerException in renewal checkout be fixed?" is classified as a bug localization task. The planner retrieves stack trace frames, similar bug reports, changed files, dependency paths, and tests that exercise the failing flow. Context planning is essential because a single similarity query may retrieve artifacts that are textually related but insufficient for engineering action.

The evidence-constrained generation layer produces answers only from retrieved evidence. Outputs are structured as decision cards containing: query interpretation, retrieved evidence, ranked candidate artifacts, reasoning chain summary, confidence estimate, recommended action, validation steps, and unresolved uncertainty. The reasoning summary is not a hidden chain of thought; it is an explicit, concise justification based on evidence. For example, a bug localization card may state that a candidate file is ranked first because it contains the top stack frame, was modified in the last release, owns the failing API route, and is linked to two similar historical defects. This design aligns with architecture-centered decision intelligence, where AI recommendations must be connected to project governance and implementation context [26].

The governance feedback layer records user interactions, accepted links, rejected links, corrected rankings, executed tests, and final resolution outcomes. This feedback is used to improve ranking, update trace links, and evaluate model performance. For regulated environments, the layer records which retrieved artifacts were visible to which user, what recommendation was made, and what evidence supported it. This is especially important in banking, healthcare, and pharmacy domains, where AI-assisted decisions may affect compliance, security, or operational safety. Cloud-native prescription automation and HIPAA-compliant prescription-processing architectures illustrate the need to combine automation with domain-specific privacy and security constraints [12].

5. Artifact Graph and Data Model

The core data structure in RASE is the enterprise software artifact graph. The graph contains typed nodes and typed edges. Node types include requirement, epic, user story, acceptance criterion, design decision, service, repository, module, file, class, method, API endpoint, database entity, configuration key, test case, commit, pull request, defect, incident, log pattern, trace span, deployment, security finding, and release approval. Edge types include implements, verifies, calls, imports, owns, depends_on, modified_by, fails_in, observed_in, duplicates, relates_to, supersedes, and governed_by.

This representation supports multi-hop retrieval. For requirement traceability, the system may start from a requirement node, retrieve semantically related code chunks, expand to tests through coverage or naming relations, and then verify links through commits and pull requests. For bug localization, the system may start from a bug report, retrieve stack trace symbols, expand to source files, follow dependency edges to downstream services, and retrieve similar historical defects. For decision support, the system may retrieve architecture decisions, risk controls, affected services, and test evidence. The graph therefore bridges requirements engineering, program comprehension, maintenance, operations, and governance.

Each node stores both raw content and normalized representations. Raw content preserves the original artifact for audit. Normalized text improves retrieval by expanding abbreviations, separating identifiers, extracting domain terms, and summarizing long code units. For source code, RASE stores lexical tokens, comments, function signatures, dependency metadata, and optional embeddings from code-aware models. For requirements, RASE stores business terms, constraints, acceptance criteria, and linked regulatory controls. For incidents, it stores symptoms, timestamps, affected services, error patterns, and resolution notes.

Temporal versioning is central. A traceability link that was valid for release 3.2 may not be valid for release 3.4. RASE therefore attaches validity intervals, branch identifiers, commit hashes, and release tags to nodes and edges. When answering a query, the planner must determine whether the user is asking about the current main branch, a production release, a hotfix branch, or a historical incident. This is particularly important for CI/CD environments where deployment velocity can cause documentation, tests, and implementation to diverge. Intelligent continuous delivery risk detection research in banking emphasizes the importance of real-world deployment evaluation, which motivates retrieval systems that understand release context [20].

Security labels are also attached to nodes and edges. A user may have access to application code but not production logs containing sensitive data. A developer may retrieve anonymized incident summaries but not raw personally identifiable information. RASE enforces policy at retrieval time, not merely at display time. Restricted chunks are excluded from candidate generation unless the user and task have authorization. This prevents the generative layer from indirectly leaking protected content. The same principle applies to federated or multi-organization settings where data cannot be centralized [8].

The graph can be built using static analysis, repository mining, natural language processing, observability integration, and human validation. Static analysis extracts call relations, imports, type references, and dependency structures. Repository mining links commits to issues, pull requests, reviewers, and release events. NLP extracts entities and constraints from

requirements and incidents. Observability integration links runtime failures to services, endpoints, and trace spans. Human validation confirms or rejects trace links and bug-localization candidates, creating a feedback loop for continuous improvement.

6. Requirement Traceability Method

Requirement traceability in RASE is formulated as a ranked evidence retrieval and link validation problem. Given a requirement or requirement clause, the system must identify implementation artifacts, verification artifacts, and governance artifacts. The input may be a new requirement, a modified requirement, a compliance rule, or a developer question about the implementation status of a feature. The output is a ranked set of candidate links with explanations and validation recommendations.

The method begins with requirement decomposition. Long requirements are split into clauses representing behavior, constraint, data condition, actor, exception, and acceptance criterion. For each clause, the system extracts domain terms, action verbs, entities, constraints, and quality attributes. It then generates multiple retrieval queries: a lexical query over exact terms, a semantic query over paraphrased meaning, and a graph query over known related artifacts. For example, a requirement mentioning "same-day reversal for duplicate ACH debit" may generate queries over "ACH," "duplicate debit," "reversal," "settlement," and related API names. Dense retrieval helps bridge vocabulary differences, while lexical retrieval preserves domain identifiers.

Candidate implementation links are retrieved from code summaries, method signatures, comments, configuration keys, database migrations, API specifications, and commits. Candidate verification links are retrieved from test names, assertions, test data, automation reports, and acceptance criteria. Candidate governance links are retrieved from architecture decision records, risk assessments, security controls, and release approvals. The system then reranks candidates using a feature set that includes semantic similarity, lexical match, identifier overlap, dependency proximity, historical co-change, ownership, recent modification, test coverage, and existing trace links.

The output is a traceability card. The card includes the requirement clause, top implementation candidates, top verification candidates, missing evidence, and suggested analyst action. A strong link may be supported by semantic similarity, identifier overlap, commit linkage, and test coverage. A weak link may be supported only by vague semantic similarity. RASE explicitly distinguishes confirmed, candidate, and speculative links. This distinction is important because automatic traceability tools can overwhelm developers if they present uncertain links as facts.

RASE also supports change impact analysis. When a requirement changes, the system retrieves linked code and tests, then expands through dependency and co-change edges to identify secondary impact. It can recommend tests to run, modules to inspect, and owners to consult. This aligns with AI-based lifecycle governance approaches that connect predictive quality assurance, cybersecurity intelligence, automation economics, and lifecycle management [24]. The difference is that RASE grounds every recommendation in retrievable artifacts rather than in a standalone model output.

Evaluation for requirement traceability should use datasets with known links or expert-labeled candidate links. Metrics include precision at k, recall at k, mean average precision, analyst effort, false negative rate for safety-critical links, and evidence sufficiency. In enterprise settings, recall is often more important than precision because missed trace links can create compliance or maintenance risk. However, high recall without ranking quality can increase analyst burden. The evaluation should therefore report both link recovery quality and review effort.

7. Bug Localization Method

Bug localization in RASE is formulated as multi-source evidence retrieval from defect descriptions, operational records, source code, history, and dependency graphs. Given a bug report, incident ticket, stack trace, log excerpt, or alert cluster, the system returns ranked candidate files, methods, services, tests, and recent changes. The method is designed for enterprise environments where defects may emerge from distributed interactions rather than from a single local code fault.

The first stage parses the defect input. The system extracts symptoms, exception types, stack frames, error codes, endpoint names, environment, release version, reproduction steps, timestamps, and affected customers or tenants when permitted. Stack frames and error codes are routed to lexical retrieval because exact symbols are highly informative. Narrative descriptions are routed to dense retrieval because developers may describe behavior using business vocabulary that differs from code names. Logs and traces are linked to service and endpoint nodes in the artifact graph.

The second stage retrieves candidates from multiple evidence sources. Source files and methods are retrieved through lexical and dense similarity. Similar historical bugs are retrieved using report text, symptoms, stack traces, and resolution metadata. Recent commits are retrieved using temporal filters and changed-file overlap. Test failures are retrieved from CI/CD records and flaky-test history. Dependency expansion identifies upstream callers, downstream services, shared libraries, and

configuration dependencies. This design extends classic IR-based bug localization by combining code, report, history, runtime, and graph evidence in a single ranking process.

The third stage reranks candidates. Features include similarity between report and code, stack trace containment, historical bug similarity, file churn, recent modification, ownership, dependency centrality, test failure association, and service proximity to runtime evidence. GraphCodeBERT-like code representations can improve semantic matching by incorporating code structure, while traditional lexical methods remain essential for exact identifiers [5]. Defect prediction research comparing machine learning models also supports the idea that different models capture different defect signals, making hybrid scoring more robust than relying on one classifier [16].

The fourth stage produces a localization card. The card lists ranked candidate files or methods, supporting evidence, likely failure mechanism, recommended validation steps, and uncertainty. For example, a candidate may be recommended because it contains the failing stack frame, was changed in the previous deployment, controls timeout recovery, and has a similar resolved defect. The card may recommend running a specific regression test, inspecting a configuration flag, or comparing behavior against the previous release. This makes localization actionable rather than merely predictive.

RASE can also integrate with incident response. During production incidents, the system can retrieve relevant runbooks, previous incidents, deployment events, feature flags, and service dependencies. Adaptive intelligence for cloud observability and automated root cause analysis motivates this operational integration [28]. For distributed systems, graph expansion can prevent narrow localization that stops at the first failing service even when the root cause lies upstream or downstream. Failure propagation modeling is therefore a key complement to code search [10].

Evaluation for bug localization should report mean reciprocal rank, top-1 accuracy, top-5 accuracy, top-10 accuracy, mean average precision, effort-aware ranking, and time-to-first-useful-candidate. It should compare RASE against lexical-only retrieval, dense-only retrieval, history-only retrieval, and graph-free hybrid retrieval. Human evaluation should ask developers whether the evidence is sufficient, whether the recommendation is actionable, and whether the system reduces debugging time. The evaluation must avoid overstating impact unless validated in realistic maintenance tasks.

8. Developer Decision Support

Developer decision support is the third RASE task and the most enterprise-specific. Developers and technical leads routinely make decisions about design alternatives, change risk, test scope, release readiness, refactoring priority, security remediation, and incident mitigation. These decisions require evidence across code, requirements, tests, dependencies, defects, and organizational constraints. A retrieval-augmented system can help only if it produces structured, evidence-grounded recommendations rather than generic advice.

RASE represents a decision as a tuple: decision question, context, alternatives, evidence, constraints, risk, recommended action, validation plan, and audit record. A decision question may be “Can this service be released without running the full regression suite?” or “Should duplicate-payment detection be implemented in the gateway or transaction service?” The context planner retrieves relevant requirements, design records, code modules, dependency paths, test history, incidents, and risk controls. The system then generates a decision card that separates factual evidence from inference.

Decision cards are designed to support human judgment rather than replace it. A card may state that alternative A has stronger alignment with existing service ownership but increases dependency coupling, while alternative B localizes business logic but requires additional test coverage. The system may recommend a validation step such as running contract tests, reviewing an architecture decision record, or consulting the owning team. This style of output aligns with decision intelligence methodology for agile software lifecycle governance and architecture-centered project management [26].

Developer decision support must also account for domain-specific operations. In pharmacy systems, for example, secure prescription processing and fax-to-digital automation require privacy, auditability, workflow reliability, and integration with cloud-native services [12]. In banking systems, fraud detection and CI/CD risk evaluation require explainability, deployment governance, and regulatory confidence [14]. RASE is not domain-specific, but it provides the evidence architecture through which domain-specific controls can be retrieved and applied.

A key design principle is that decision support should expose uncertainty. If retrieved evidence is incomplete, stale, or contradictory, the system should say so. If a recommendation depends on a test report from an outdated branch, that limitation must be visible. If a code owner has changed, the system should not silently rely on historical ownership. This uncertainty-aware behavior distinguishes enterprise decision support from simple answer generation.

Evaluation of decision support should use scenario-based studies. Participants can be asked to perform maintenance, release, or design tasks with and without RASE. Measures include decision correctness, evidence completeness, time on task,

confidence calibration, number of missed risks, and perceived usefulness. The study should also measure whether developers over-trust the system. A strong decision-support tool should improve evidence access while preserving developer accountability.

9. Retrieval, Ranking, and Generation Pipeline

The RASE pipeline begins with query classification. The system classifies user input into task categories such as traceability, bug localization, impact analysis, test recommendation, architecture decision, incident support, or release governance. Classification determines which artifact types and retrieval strategies are activated. A traceability query emphasizes requirements, code, tests, and acceptance criteria. A bug localization query emphasizes bug reports, stack traces, source files, commits, tests, and logs. A release decision query emphasizes CI/CD outcomes, recent changes, risk controls, and deployment history.

Next, the system performs query rewriting. Software engineering queries often contain abbreviations, internal terminology, and partial identifiers. RASE expands identifiers, splits compound names, normalizes stack traces, and generates paraphrases. For code search, natural language and programming language vocabulary must be bridged, a challenge highlighted by the CodeSearchNet benchmark [17]. Query rewriting therefore creates multiple query variants rather than relying on one phrasing.

Hybrid retrieval then runs in parallel. BM25-style lexical retrieval handles exact terms, symbols, and identifiers [7]. Dense retrieval handles semantic similarity between requirements, bug descriptions, code summaries, and documentation. Graph retrieval expands candidates through typed relations. Temporal retrieval filters by release, branch, incident window, or deployment. The results are merged using reciprocal rank fusion or learned ranking. RASE intentionally retains lexical retrieval because enterprise terms, error codes, and proprietary identifiers are often decisive.

Candidate reranking uses richer features than initial retrieval. A cross-encoder can score query-candidate pairs when latency permits. Code-aware models can compare natural language requirements to code summaries. Graph features measure dependency proximity, ownership, and co-change. Temporal features identify recent changes and release alignment. Governance features penalize stale or unauthorized artifacts. The reranker produces a candidate set with evidence scores and explanations.

Generation is then conditioned on the top evidence. The generator receives the user query, task type, retrieved artifacts, metadata, and output schema. It is instructed to cite evidence identifiers, avoid unsupported claims, state uncertainty, and recommend validation. The output is not free-form chat; it is a structured engineering artifact such as a traceability card, localization card, or decision card. The card can be attached to a ticket, pull request, incident record, or architecture review.

Feedback closes the loop. Developers can mark recommendations as useful, incorrect, incomplete, or stale. They can confirm trace links, reject bug candidates, attach missing evidence, or update ownership. These actions update the artifact graph and training data. Over time, the system learns repository-specific vocabulary, service boundaries, defect patterns, and decision preferences. AI-driven software lifecycle frameworks have emphasized continuous governance feedback; RASE operationalizes that feedback through retrieval evidence and artifact graph updates [2].

10. Governance, Security, and Enterprise Deployment

Enterprise deployment requires more than retrieval accuracy. RASE must satisfy governance, privacy, security, auditability, and operational reliability requirements. The system may index sensitive code, production logs, customer-impacting incidents, regulated workflows, and security findings. Therefore, governance must be designed into the architecture.

Access control is enforced at ingestion, indexing, retrieval, and generation. At ingestion, artifacts are labeled according to repository permissions, data sensitivity, regulatory scope, and tenant boundaries. At indexing, sensitive chunks may be encrypted, isolated, or represented only through sanitized summaries. At retrieval, user identity and task context determine what can be retrieved. At generation, the model can use only authorized retrieved content. The system also logs which artifacts influenced each recommendation. Secure microservices architecture research in healthcare-like prescription contexts underscores that cloud-native automation must remain compliant with domain-specific privacy and security constraints [4].

Auditability is provided through evidence contracts. Every generated recommendation contains references to retrieved artifacts, ranking rationale, and validation steps. The system stores the retrieval query, candidate set, selected evidence, model version, and user action. This makes it possible to review why a recommendation was made and whether it relied on stale or unauthorized information. Explainable AI work in regulatory-grade fraud detection motivates this emphasis on auditable decision pathways [14].

Data governance is also necessary for model training and feedback. Developer feedback can contain sensitive information, so feedback logs must be protected. If multiple business units or institutions collaborate, federated approaches may be needed to avoid centralizing restricted data [8]. RASE can support federated retrieval by maintaining local indexes and exchanging only policy-approved summaries or embeddings, although this requires careful leakage analysis.

Operational deployment should be incremental. A low-risk first phase can index documentation, code summaries, and non-sensitive tickets. A second phase can add source-level code retrieval, tests, and build metadata. A third phase can integrate incidents, logs, and security findings under stronger access controls. This phased deployment allows organizations to validate usefulness and governance controls before indexing highly sensitive data.

RASE also requires human process integration. The system should appear in developer environments where decisions occur: IDEs, pull requests, issue trackers, incident platforms, CI/CD dashboards, and architecture review workflows. It should not require developers to switch to a separate knowledge portal for every question. Developer adoption depends on low latency, useful ranking, concise evidence, and trust calibration.

11. Evaluation Protocol

A rigorous evaluation of RASE should include offline retrieval benchmarks, controlled developer studies, and longitudinal field evaluation. Offline benchmarks provide repeatability. Developer studies measure usefulness and decision quality. Field evaluation measures adoption and operational impact. This paper defines the protocol so that future work can execute it without inventing unsupported results.

For requirement traceability, the dataset should include requirements, code, tests, commits, and known trace links. Open-source systems with issue-to-commit links can be used as proxies, while industrial datasets can provide stronger ecological validity. The task is to retrieve implementation and verification artifacts for each requirement. Baselines should include lexical retrieval, dense retrieval, existing trace links, and hybrid retrieval without graph expansion. Metrics should include recall at k, precision at k, mean average precision, analyst review effort, and missing critical link rate.

For bug localization, the dataset should include bug reports, fixed files, commits, tests, and optional logs. Classic bug-localization datasets can be complemented with modern service-oriented repositories. Baselines should include BugLocator-like lexical/history retrieval, structured IR, dense code retrieval, and graph-free hybrid retrieval. Metrics should include top-1, top-5, top-10 accuracy, mean reciprocal rank, mean average precision, and effort-aware rank. The evaluation should distinguish between file-level and method-level localization because method-level localization is more useful but harder.

For decision support, evaluation should use realistic scenarios created from historical engineering decisions. Participants can be asked to perform impact analysis, release risk assessment, test selection, or incident triage. The study should compare no assistant, generic search, generic LLM, and RASE decision cards. Measures should include correctness, evidence sufficiency, time on task, missed risk count, confidence calibration, and perceived usefulness. The study should record whether participants accept unsupported recommendations, because over-trust is a serious risk.

Ablation studies are essential. The evaluation should remove lexical retrieval, dense retrieval, graph expansion, temporal filtering, reranking, and evidence contracts one at a time. This reveals which components matter for each task. For example, lexical retrieval may dominate stack-trace localization, dense retrieval may improve requirement-code matching, and graph expansion may improve incident triage. Code model ablations should compare general text embeddings with code-aware embeddings and structure-aware representations.

The protocol should also include latency and scalability. Indexing time, query latency, memory usage, and retrieval throughput matter in enterprise environments. Large-scale code corpora such as The Stack demonstrate the feasibility and complexity of managing massive code datasets for language-model research [25]. Enterprise deployments may not reach that scale, but they require freshness, access control, and incremental indexing.

Finally, evaluation must include governance metrics. These include unauthorized retrieval rate, provenance completeness, stale evidence rate, hallucinated evidence rate, and audit replay success. Secure development guidance emphasizes repeatable practices for reducing software vulnerability risk across the lifecycle [27]. A retrieval-augmented engineering system should therefore be judged not only by relevance but also by whether it supports safe and auditable engineering practice.

12. Discussion

RASE reframes enterprise software engineering knowledge as an active retrieval substrate. This is different from traditional documentation search, which assumes that the user knows what to search for and how to interpret results. In RASE, the system plans retrieval according to task context, combines evidence across artifacts, and produces structured decision

support. The central benefit is not that the system "knows" the codebase in a human sense, but that it can rapidly assemble relevant evidence that humans can inspect.

The framework also clarifies the role of generative AI in software engineering. Generative models should not be treated as independent authorities over enterprise code. Their value comes from summarizing, connecting, and operationalizing retrieved evidence. This distinction matters because enterprise codebases contain proprietary patterns, evolving architectures, and regulated constraints that may not be represented in pretrained model parameters. Retrieval makes the system updateable, auditable, and organization-specific.

RASE also supports a broader shift from artifact management to decision governance. Requirements, defects, tests, and incidents are often managed in separate systems, but engineering decisions cut across them. A release decision may depend on changed requirements, modified code, failed tests, unresolved incidents, and compliance controls. A retrieval-augmented decision card makes these dependencies visible. AI architecture work on innovation, lifecycle optimization, and cybersecurity risk mitigation reinforces the importance of converged architectures rather than isolated AI tools [18].

The framework is especially relevant for regulated enterprise domains. Banking, healthcare, pharmacy, insurance, and public-sector systems require traceability, auditability, and risk justification. Research on fraud detection, privacy-preserving learning, and regulated explainability provides adjacent evidence that AI systems in such domains must be transparent and governed [14]. RASE translates those principles into software engineering by making evidence and provenance explicit in every recommendation.

At the same time, RASE has limitations. Retrieval quality depends on artifact quality. If requirements are vague, commits are poorly linked, tests are undocumented, and logs are inconsistent, retrieval will be weaker. The system can expose these gaps but cannot fully solve them. RASE may also increase cognitive load if it returns too much evidence. Therefore, ranking, summarization, and uncertainty display are critical user-interface problems.

Another limitation is model drift. Codebases change rapidly, and stale indexes can produce incorrect recommendations. Incremental indexing and temporal metadata reduce this risk but do not eliminate it. The system must clearly state the freshness of evidence and avoid answering from outdated artifacts when current artifacts are unavailable. In CI/CD settings, retrieval freshness may need to be measured in minutes rather than days.

Finally, organizations must manage the social consequences of AI decision support. Developers may resist tools that appear to monitor productivity or override expertise. RASE should be positioned as evidence support, not surveillance or replacement. Human validation, transparent feedback, and local team control are essential for adoption.

13. Threats to Validity

Construct validity concerns whether the proposed metrics capture meaningful engineering outcomes. Retrieval metrics such as precision and recall are necessary but insufficient. A highly ranked file may be technically relevant yet not useful for a developer's task. Therefore, the evaluation protocol includes human measures such as actionability, evidence sufficiency, and time on task. Still, these measures can be subjective and must be collected through carefully designed instruments.

Internal validity concerns whether observed improvements are caused by RASE rather than by confounding factors. In developer studies, participant experience, repository familiarity, task difficulty, and tool familiarity can influence outcomes. Randomized task assignment, counterbalancing, and baseline comparisons are necessary. For offline experiments, leakage can occur if fixed files are indirectly encoded in commit messages or issue links. Dataset construction must prevent unrealistic access to future information.

External validity concerns whether results generalize across organizations and domains. Enterprise codebases vary by language, architecture, process maturity, documentation quality, and regulatory environment. A system that works well for Java microservices may perform differently for legacy mainframe systems or embedded software. The evaluation should therefore include multiple repositories, languages, and artifact ecosystems.

Conclusion validity concerns whether statistical findings are reliable. Many software engineering datasets are imbalanced; most files are not relevant to a given bug or requirement. Reporting only top-k accuracy may obscure effort costs or false positives. Confidence intervals, effect sizes, and non-parametric tests should be used where appropriate. Longitudinal field studies should avoid attributing broad productivity gains to RASE without controlling for process changes.

Ethical and security validity also matter. A retrieval system can expose sensitive code, logs, or personal data if access control is weak. It can also produce overconfident recommendations that developers follow without sufficient review. RASE

addresses these risks through policy-aware retrieval, evidence contracts, audit logs, and uncertainty reporting, but implementation errors remain possible.

14. Conclusion

This paper proposed RASE, a retrieval-augmented software engineering framework for enterprise codebases. The framework addresses three evidence-intensive tasks: context-aware requirement traceability, bug localization, and developer decision support. RASE combines artifact-aware ingestion, typed software artifact graphs, hybrid lexical–dense retrieval, graph expansion, temporal filtering, evidence-constrained generation, and governance feedback. The central design principle is that enterprise AI assistance must be grounded in retrievable, inspectable, authorized, and version-aware engineering evidence.

The paper contributes a research artifact and an evaluation protocol rather than unsupported empirical claims. The protocol defines research questions, baselines, metrics, ablations, developer studies, and governance measures. Future work should instantiate RASE in industrial environments, evaluate it on multi-repository enterprise systems, and study its effect on traceability quality, debugging efficiency, release governance, and developer trust. The long-term opportunity is to transform enterprise software engineering from fragmented artifact search into auditable, context-aware, evidence-centered decision support.

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