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Original Article

Autonomous Code Review Using Large Language Models: A Hybrid Framework for Code Quality Assessment, Refactoring Recommendation, and Technical Debt Reduction

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ABSTRACT: *Autonomous code review is emerging as a critical software engineering capability because modern teams must inspect increasingly large pull requests, multi-service dependencies, and AI-generated code changes without weakening security, maintainability, or delivery speed. This paper proposes ARC-TD, a hybrid large language model framework for code quality assessment, refactoring recommendation, and technical debt reduction. Unlike purely generative reviewers that comment directly on code diffs, ARC-TD combines static analysis, repository-aware retrieval, dependency graph reasoning, risk-calibrated LLM review, test-aware validation, and human governance into a single decision pipeline. The framework represents code review as a multi-objective optimization problem in which defects, maintainability risks, refactoring safety, architectural drift, and debt repayment value are jointly estimated. The proposed methodology defines review units, retrieves local and historical context, generates structured findings, verifies proposed refactorings against rules, tests, and semantic constraints, and prioritizes debt items using severity, propagation risk, remediation cost, and business-criticality signals. The paper presents the architecture, scoring model, review workflow, governance controls, evaluation protocol, and implementation considerations for enterprise deployment. The central contribution is a research-grade design that treats LLMs not as autonomous committers, but as bounded reasoning agents whose outputs are constrained by static evidence, historical review knowledge, quality gates, and reviewer feedback. The resulting framework aims to improve review consistency, reduce low-value reviewer effort, and transform technical debt management from episodic clean-up into continuous, evidence-grounded remediation.*

KEYWORDS: *Large Language Models, Autonomous Code Review, Static Analysis, Retrieval-Augmented Generation, Refactoring, Technical Debt, Software Quality, Devsecops, Software Maintenance.*

TABLE 1 Evaluation Research Questions and Measures

Research Question	Primary Measure	ARC-TD Evidence
RQ1: Does ARC-TD improve review usefulness?	Accepted useful comment rate; false-positive rate	Developer action labels and reviewer edits
RQ2: Does ARC-TD reduce effort?	Review latency and reviewer comment load.	Pull-request timestamps and comment grouping
RQ3: Does ARC-TD improve quality?	Pre-merge defects found and test gaps closed	Static findings, tests, and semantic validation
RQ4: Does ARC-TD reduce debt?	Severity-weighted debt density over releases	Debt ledger, accepted refactorings, and recurrence trends

1. INTRODUCTION

Code review has moved from a late-stage inspection activity to a continuous control point for software reliability, security, and maintainability. In cloud-native and API-driven systems, small code changes can propagate across service contracts, persistence layers, observability pipelines, and deployment policies. Conventional reviewer workflows are therefore under pressure: reviewers must understand implementation details while also judging architectural consistency, regression risk, performance impact, and long-term maintainability. The proposed study positions autonomous review as a decision-support system rather than a replacement for human accountability, aligning review automation with fault prediction and robustness objectives in software quality engineering [1].

Enterprise development environments increasingly rely on container orchestration, deployment templates, feature flags, and service mesh controls, which makes review quality dependent on operational context as much as source-level correctness. A pull request may satisfy syntax and unit testing constraints but still introduce deployment fragility, missing telemetry, excessive coupling, or unsafe rollout behavior. For this reason, ARC-TD integrates code review with DevOps evidence and infrastructure metadata so that recommendations remain deployable rather than abstract. Deployment optimization research supports this view by showing that review and release quality should be evaluated alongside runtime platform characteristics [2].

The rise of AI-assisted coding has intensified the need for stronger review automation. LLM-generated code can be syntactically plausible and locally functional while still duplicating logic, hiding architectural assumptions, weakening exception handling, or increasing future maintenance burden. A credible autonomous reviewer must therefore evaluate not only whether code compiles, but whether it remains understandable, testable, secure, and consistent with project conventions. The architecture proposed here extends quality engineering principles from end-to-end validation into code review by making review output traceable to evidence and testable quality objectives [3].

Technical debt is especially difficult to manage because many debt items are rationalized as small compromises under delivery pressure. Teams often accept duplicated branches, oversized methods, weak naming, inconsistent error models, or missing abstraction boundaries because each individual issue appears minor. Over time, these issues compound into reduced changeability and higher regression risk. ARC-TD treats debt as a measurable portfolio of localized and systemic liabilities, using caching, telemetry, and usage signals to prioritize items whose correction is likely to deliver measurable engineering value [4].

Software defect prediction research demonstrates that quality risk can be estimated from code metrics, change history, and learned patterns, yet such predictions are rarely integrated directly into daily review conversations. This separation creates a gap between predictive analytics and developer action. The paper addresses that gap by embedding defect-risk signals within review comments and refactoring recommendations, allowing the reviewer to see not merely that a construct is suspicious but why it is risky in relation to historical failures, complexity, churn, or dependency sensitivity [5].

Recent technical-debt remediation work indicates that LLMs are promising when their refactorings are validated rather than accepted directly. ARC-TD adopts this principle by generating candidate transformations, validating them with static rules and tests, and rejecting changes that alter externally observable behavior. The system is intentionally hybrid because LLM reasoning is valuable for explanation and synthesis, while deterministic tools are essential for precision, repeatability, and governance. This hybrid stance forms the central research thesis of the paper [6].

2. RESEARCH CONTEXT AND GAP

Automated review research has historically focused on style violations, defect-prone files, reviewer recommendations, and generated comments. However, modern enterprise review requires richer reasoning across API contracts, financial or healthcare workflow integrity, data validation, and operational resilience. API reliability studies show that code quality is inseparable from transaction correctness, idempotency, and failure handling. ARC-TD incorporates these concerns by linking review findings to concrete risk categories such as data loss, retry inconsistency, contract drift, and auditability gaps [7].

Machine learning optimization methods provide useful analogies for autonomous review because code quality assessment is not a single-label classification task. The reviewer must balance precision, recall, false-positive cost, severity, remediation effort, and developer trust. Evolutionary optimization work on model structure highlights the need to search across competing objectives instead of optimizing a single score. ARC-TD therefore uses a weighted utility function that can be tuned by repository maturity, compliance burden, and release criticality [8].

Deep learning models for software fault prediction demonstrate the value of learning temporal and structural patterns from code, but code review adds a further requirement: the system must explain actionable fixes in a developer-readable manner. A fault predictor can classify a file as risky, but a reviewer needs location, rationale, suggested remediation, and confidence. ARC-TD addresses this difference by combining metric-driven risk scoring with LLM-generated explanations and refactoring candidates that are traceable to the triggering evidence [9].

Automation in regulated domains provides another lesson for code review: recommendations must be auditable. In prescription automation, for example, OCR and machine learning components are useful only when deployed with process controls, exception handling, and traceability. Similarly, code-review automation must preserve the rationale behind comments, the evidence used for retrieval, and the validation status of proposed changes. ARC-TD records each finding as a structured artifact containing evidence, model reasoning, severity, and resolution history [10].

The use of high-performance computing and simulation in scientific workflows suggests that autonomous review should be designed for scale. Repository-level review can involve thousands of files, dependency graphs, generated code, configuration files, and test artifacts. Instead of sending entire repositories into an LLM context window, ARC-TD creates compact review units and retrieves only the most relevant semantic, syntactic, and historical context. This design allows the framework to operate under practical cost, latency, and privacy constraints [11].

Industrial work on AI-assisted code review shows both promise and caution. Automated comments can detect best-practice violations and provide early feedback, but they may also create noise if they lack project context or fail to differentiate low-severity style matters from architectural concerns. ARC-TD responds by including a review filter that suppresses low-confidence comments, groups duplicate findings, and routes high-risk findings to human reviewers with evidence summaries. The goal is not more comments, but better review attention allocation [12].

3. RESEARCH PROBLEM, OBJECTIVES, AND CONTRIBUTIONS

The core research problem is how to design an autonomous review framework that can produce useful, safe, and auditable recommendations without over-relying on generative output. A system that merely asks an LLM to review a diff is vulnerable to hallucination, style drift, missing repository conventions, and unvalidated refactoring. ARC-TD formulates code review as an evidence-constrained reasoning task in which each generated comment must be linked to source facts, code metrics, rule findings, dependency impact, or historical review examples [13].

The first objective is to improve code quality assessment by fusing static analysis, learned risk models, code embeddings, and repository-specific retrieval. The second objective is to recommend refactorings that are behavior-preserving, locally applicable, and economically justified. The third objective is to reduce technical debt by prioritizing issues that impose long-term maintenance costs rather than merely highlighting every rule violation. Numerical stability research offers a useful analogy: an algorithm is valuable only if its convergence and implementation properties are understood, not just its theoretical output [14].

This paper contributes a hybrid architecture, a technical-debt scoring model, an autonomous review workflow, a refactoring validation loop, and an enterprise governance model. The framework is designed to be implemented in pull-request systems, CI/CD pipelines, and developer IDE workflows. It supports incremental adoption, beginning as an advisory reviewer and evolving toward semi-autonomous remediation for low-risk changes. Comparative defect-prediction research motivates this design by demonstrating that different models capture different risk signals, making hybridization preferable to a single model assumption [15].

The paper is not a review manuscript; it proposes a research framework and operational methodology. The novelty lies in joining LLM-based reasoning with static evidence, retrieval, quality gates, and debt economics inside a repeatable code-review process. The proposed evaluation protocol measures comment usefulness, defect detection, review latency, technical-debt reduction, and developer acceptance. Cloud platform comparison studies reinforce the need to evaluate software solutions under operational deployment constraints rather than isolated algorithmic benchmarks alone [16].

4. PROPOSED ARC-TD FRAMEWORK

ARC-TD contains six layers: ingestion, representation, retrieval, reasoning, validation, and governance. The ingestion layer collects the diff, changed files, dependency metadata, build scripts, tests, security findings, ownership records, and relevant historical review comments. The representation layer converts these artifacts into structured review units using abstract syntax trees, control-flow summaries, code embeddings, and dependency edges. Identifier-aware code models are especially useful here because variable and method names often carry domain semantics that generic token models underuse [17].

The retrieval layer constructs a repository-aware evidence bundle for each review unit. It retrieves similar historical diffs, coding guidelines, prior defects, API contract documentation, test failures, and architectural decision records. Retrieval is not used as a passive knowledge add-on; it is used as a boundary condition for model reasoning. The reviewer prompt is therefore grounded in what the project has already accepted or rejected. In distributed systems, this is analogous to dynamic service composition, where local decisions must account for surrounding dependencies [18].

The reasoning layer uses an LLM to synthesize review findings, but the model receives a constrained schema rather than an open-ended request. Each finding must specify issue type, location, evidence, severity, confidence, proposed change, likely side effect, and validation requirement. The framework rejects findings that cannot be grounded in retrieved or static evidence. Neural-network optimization research suggests that model performance improves when training and inference are guided by explicit structure; ARC-TD applies the same principle at the workflow level [19].

The validation layer executes deterministic checks before any recommendation is surfaced as actionable. Static rules confirm that the issue exists, tests verify behavior, semantic diffs compare before-and-after intent, and repository policies decide

whether the finding should block a merge or remain advisory. The framework also checks whether a proposed refactoring violates clean-core principles, especially in enterprise platforms where custom extensions must not compromise upgrade paths or platform maintainability [20].

TABLE 2 ARC-TD Framework Components

Layer	Input	Method	Output
Ingestion	Diffs, tests, rule findings, ownership	Incremental repository analysis	Review units and metadata
Representation	ASTs, embeddings, dependency graphs	Static parsing and code-model encoding	Semantic code profiles
Retrieval	Guidelines, previous reviews, and incidents	Hybrid semantic and keyword retrieval	Evidence bundles
Reasoning	Evidence bundles and quality schema	LLM constrained generation	Structured candidate findings
Validation	Candidate findings and patches	Static rules, tests, and semantic diffing	Validated or rejected actions
Governance	Reviewer decisions and outcomes	Calibration and audit logging	Trust, thresholds, and debt ledger

The governance layer manages reviewer trust. It stores comment outcomes, developer responses, false-positive labels, accepted refactorings, and rollback incidents. These signals train repository-specific calibration models and update thresholds for future recommendations. Decision intelligence work in agile lifecycle governance motivates this feedback-oriented design because software governance must connect prediction, decision, and action rather than treating analytics as a separate reporting layer [21].

ARC-TD represents every review finding as a tuple F = <u, e, r, s, c, v>, where u is the review unit, e is the evidence bundle, r is the risk category, s is the severity score, c is the confidence score, and v is the validation status. This structured representation makes findings searchable, auditable, and measurable across releases. OCR accuracy work in healthcare illustrates why validation status is important: a model prediction is insufficient unless downstream systems know whether it has been checked, corrected, or approved [22].

The review workflow begins when a pull request is opened or updated. The system computes incremental metrics, identifies changed review units, retrieves context, generates candidate findings, validates them, groups duplicates, and produces a ranked review summary. Human reviewers can accept, dismiss, edit, or request automated patch generation. Retrieval-augmented generation is central because the LLM must rely on project-specific evidence rather than generic coding advice when assessing whether a pattern is acceptable in the repository [23].

A key design decision is to separate finding generation from patch generation. The framework can identify a risk without immediately rewriting code. When a patch is generated, it is treated as a candidate refactoring that must pass tests and semantic checks. This separation reduces the chance that the system introduces new errors while trying to fix old ones. Agentic AI governance work reinforces the importance of trust controls, lifecycle reliability, and grounded decision-making in autonomous enterprise systems [24].

5. HYBRID CODE QUALITY ASSESSMENT MODEL

ARC-TD evaluates code quality using a multi-dimensional model rather than a single maintainability index. The primary dimensions are correctness risk, security exposure, maintainability, testability, readability, performance sensitivity, observability, and architectural consistency. Each dimension is scored using static features, historical defect density, dependency impact, and LLM explanation confidence. Sparse matrix factorization concepts are relevant because large repositories contain sparse relationships among files, owners, defects, and dependencies that must be modeled efficiently [25].

The quality score for a review unit is defined as $Q(u) = w1C + w2S + w3M + w4T + w5A + w6O$, where C denotes correctness risk, S security exposure, M maintainability risk, T test adequacy, A architectural alignment, and O operational observability. The weights are not fixed globally; they are calibrated by repository type and release criticality. Feature model integrity research supports this approach because software product-line quality depends on the consistency of constraints and variation points [26].

Maintainability assessment includes cyclomatic complexity, cognitive complexity, nesting depth, duplicated code, dead branches, long parameter lists, unstable dependencies, naming inconsistency, and exception-handling patterns. LLMs add value by explaining why these patterns matter in the specific domain rather than merely reporting a rule violation. In SAP and

enterprise transitions, similar challenges appear when teams must modernize without breaking customization boundaries, showing that maintainability must be assessed in relation to platform evolution [27].

Correctness risk is estimated using change size, churn, historical defect density, touched interfaces, branch coverage, test proximity, and semantic distance from prior versions. The LLM examines whether the code change violates domain assumptions, boundary conditions, null handling, idempotency, or transaction guarantees. Empirical fault-prediction comparisons justify using multiple learners and feature families, because tree-based, linear, and distance-based models often capture different aspects of defect-prone behavior [28].

Testability is evaluated by mapping changed code to existing tests, identifying missing boundary scenarios, and detecting untested failure paths. The framework recommends test additions when a finding cannot be safely resolved through code refactoring alone. Automated testing research in Java enterprise systems is relevant because review quality is deeply tied to the ability to validate behavior under unit, integration, and regression scopes. ARC-TD therefore treats test recommendations as first-class review outputs rather than secondary suggestions [29].

Code representations are generated using a combination of token embeddings, syntax features, dependency graphs, and rule-based summaries. CodeBERT-like models provide useful language-code alignment for comment generation and semantic search, especially when review questions connect natural-language requirements with implementation details. ARC-TD uses such models to retrieve similar prior code patterns and to detect semantic similarity across refactored implementations without depending solely on textual matching [30].
Backend modernization is often constrained by service contracts and legacy compatibility. A code reviewer must recognize when a new abstraction improves local readability but weakens compatibility or operational simplicity. For this reason, ARC-TD checks whether recommended changes alter public interfaces, serialization formats, error codes, retry semantics, or database migration assumptions. Backend-agent replacement work motivates the need to evaluate AI recommendations against integration realities rather than isolated code fragments [31].

6. REFACTORING RECOMMENDATION METHODOLOGY

The refactoring module converts validated findings into candidate transformations. It supports the extract method, rename symbol, introduce parameter object, replace conditional with polymorphism, consolidate duplicate logic, strengthen exception typing, add guard clauses, and decouple service dependencies. Each recommendation includes a precondition, expected benefit, risk, and validation plan. Scalable and explainable AI frameworks in CRM contexts show that recommendations must be both technically effective and interpretable to stakeholders who manage platform risk [32].

ARC-TD classifies refactorings into safe, guarded, and architectural categories. Safe refactorings are local and behavior-preserving; guarded refactorings require targeted regression tests; architectural refactorings require design review and cannot be auto-applied. This classification prevents the system from treating all improvements as equal. Edge-cloud optimization research demonstrates the value of matching decision automation to resource and deployment context, a principle that also applies to deciding when code changes should be autonomous or human-reviewed [33].

For each candidate refactoring, the system performs semantic differencing. It compares public signatures, side effects, exception paths, data-flow relationships, and test outcomes. A change is rejected if it improves a metric while weakening behavior or observability. Privacy-preserving federated learning work is relevant because it shows that distributed systems can benefit from shared learning while preserving institutional boundaries; ARC-TD similarly supports organization-wide learning without exposing sensitive code across repositories [34].

The framework also supports debt-aware refactoring prioritization. A code smell is not automatically worth fixing; the decision depends on future change likelihood, defect correlation, ownership, customer impact, and remediation cost. ARC-TD estimates repayment value as R = (severity x change-frequency x propagation-risk x business-criticality) / remediation-effort. Ethical optimization research cautions that efficiency should not be the only target, so the model also considers fairness in reviewer workload and maintainability for future teams [35].

Repository observability improves refactoring safety. If the system knows which pipeline, data feed, or service boundary a code region supports, it can recommend additional telemetry or rollback checks alongside the code change. Automated monitoring work for data pipelines motivates this integration because remediation is safer when the system can observe the effects of changes after deployment. ARC-TD therefore links refactoring suggestions with observability tasks when runtime impact is plausible [36].

The LLM is prompted to explain refactoring intent using concise engineering language: problem, evidence, change, validation, and expected impact. This avoids generic comments such as 'improve readability' and instead produces actionable guidance such as 'extract the eligibility calculation because three branches repeat the same null and status checks and the duplicated

logic has diverged in two prior defects.' The expanding role of ML models in software development supports this movement from passive prediction to developer-facing decision assistance [37].

ARC-TD includes a rollback-aware patch proposal process. Candidate patches are generated in isolated branches, tested, compared, and summarized for review. If accepted, the system records the outcome and monitors post-merge incidents. Secure microservices work in regulated prescription processing show that architecture changes must be evaluated for compliance, interface stability, and deployment controls. These concerns make rollback planning and evidence retention essential in autonomous refactoring [38].

7. TECHNICAL DEBT REDUCTION MODEL

Technical debt reduction in ARC-TD is continuous rather than campaign-based. Each pull request is evaluated for debt introduced, debt removed, and debt deferred. The system maintains a debt ledger that links findings to files, owners, affected services, severity, and estimated repayment cost. Automated review-comment generation research shows that pre-trained models can produce useful review guidance, but ARC-TD extends comment generation into debt tracking and repayment prioritization [39].

Debt categories include code debt, test debt, architecture debt, documentation debt, observability debt, security debt, and deployment debt. The framework avoids over-focusing on style because style-only findings can reduce trust if they crowd out bigger risks. Enterprise chatbot work is relevant because it highlights the importance of ethical and industry-specific constraints in AI systems. Similarly, debt recommendations must respect team conventions, regulatory context, and developer attention limits [40].

Debt is scored at both local and systemic levels. A long method may be a local issue, while repeated transaction validation logic across services is systemic. ARC-TD detects systemic debt by clustering similar findings across repositories and by analyzing dependency graphs. In healthcare customer-journey mapping, deep learning models are used to identify patterns across processes; ARC-TD applies a similar pattern-recognition mindset to discover recurring maintainability risks across codebases [41].

The framework uses a debt burn-down metric that measures the reduction in high-priority debt density over time. This metric is more meaningful than counting closed comments because it weights issues by severity and propagation risk. Adaptive service-fabric research illustrates how resource management can be dynamic and context-aware. ARC-TD uses the same principle to adapt thresholds: repositories with high release risk receive stricter debt gates than exploratory prototypes [42].

Debt reduction must remain compatible with agile governance. ARC-TD therefore supports three modes: advisory mode, gate mode, and remediation mode. Advisory mode posts non-blocking recommendations, gate mode blocks severe validated issues, and remediation mode opens candidate patches for low-risk refactorings. AI-driven lifecycle governance research supports this gradual adoption because engineering teams need a controlled path from insights to operational policy [43].

Root-cause reasoning is important because recurring debt often indicates process weakness rather than isolated developer mistakes. If the same service repeatedly accumulates missing tests, exception inconsistencies, or duplicated validation logic, the framework recommends structural interventions such as shared libraries, review templates, or ownership changes. Cloud observability and automated root-cause analysis research support this shift from symptom reporting to causal remediation in complex systems [44].

8. EVALUATION DESIGN AND METRICS

The proposed evaluation is organized around five research questions: whether ARC-TD improves the useful finding rate, whether it reduces reviewer effort, whether it improves defect detection, whether it reduces high-priority technical debt, and whether developers trust its recommendations. The evaluation should be conducted across repositories with different languages, service types, and maturity levels. Digital transformation research in healthcare reinforces the need for evaluation designs that combine process metrics with technical outcomes [45].

The first metric is useful comment rate, defined as the proportion of automated findings that developers accept, act on, or mark as helpful. The second is the false-positive rate, measured by dismissed findings with no corrective action. The third is review latency, measured from pull-request opening to approval. Predictive monitoring research for change-data-capture pipelines motivates the use of early-warning metrics because code review should detect likely failure patterns before they reach production [46].

The fourth metric is defect-prevention yield, measured by the number of validated defects, missing tests, or risky changes detected before merge. The fifth metric is debt repayment value, computed from severity-weighted debt removed during the

review cycle. Predictive validation work on banking transaction workflows supports using domain-sensitive defect models because the cost of an escaped issue varies by transaction criticality, audit requirements, and user impact [47].

Security and compliance metrics include secrets exposure, insecure deserialization, weak authorization checks, missing input validation, unsafe logging, and data-in-transit risks. The system should classify whether findings are generated by static rules, LLM reasoning, or combined evidence. Secure fax communication research is relevant because it shows that anomaly detection and encryption concerns must be evaluated with operational compliance in mind rather than generic software metrics alone [48].

Structural evaluation should include semantic code similarity, data-flow consistency, and dependency impact. Graph-aware code representations help identify whether a refactoring preserves variable relationships and value flows even when names or local structure change. GraphCodeBERT-like approaches are therefore suitable for representing semantics beyond token order. ARC-TD can use these representations to compare candidate patches and reject transformations that disrupt important data-flow relationships [49].

Industry evaluation should include developer surveys, qualitative interviews, and longitudinal trend analysis. The framework should measure whether reviewers spend more time on architecture and domain correctness after low-level issues are filtered. Anomaly detection in insurance contexts illustrates how AI systems can support domain-specific risk detection, but evaluation must include human acceptance because an accurate model that developers ignore will not improve outcomes [50].
A controlled study can compare three review conditions: manual review only, generic LLM review, and ARC-TD hybrid review. Outcome measures should include accepted defects found, duplicate comments, average closure time, post-merge incidents, and high-priority debt density. Decision-intelligence frameworks in Salesforce enterprise platforms support the broader methodological idea that predictive and prescriptive analytics should be evaluated by decision outcomes, not only model-level accuracy [51].

9. IMPLEMENTATION BLUEPRINT AND ENTERPRISE DEPLOYMENT

A practical ARC-TD deployment begins with read-only analysis. In this stage, the system observes pull requests, produces private review summaries, and compares its findings against human reviewer outcomes without posting comments. This shadow period sets false-positive ground truth, repository-specific vocabulary, code patterns, and risk thresholds. Along with enabling security teams to authenticate, prompt redaction, access controls, retention policies, and model-routing rules even before developers interact with the system themselves.

Advisory comments for low-risk categories like duplicated validation (or 2nd stage), missing boundary tests, inconsistent exception handling, and unclear naming around changed logic are enabled at the second stage of deployment. All advisory comments should be compiled into one review summary, not dispersed across every line, as too much feedback at the line-level makes things harder for our brains to process. Developers should also be able to expand each finding to view evidence, pulled examples, and the status of validation, while the default view would focus on top-value actions.

Quality gates for policy-aligned, deterministic, validated findings only at stage 3. Or it could be as simple as an example, such as new secrets, broken security rules, testing in required tests for high-risk components not passing, and breaking public API changes. And then let me remind you that ARC-TD should not block a merge just because of stylistic opinions from the LLMs. Such a separation keeps reviewer trust intact by allowing blocking power only for findings that can be explained and replicated, which are serious enough to warrant any delivery friction.

The fourth stage enables automated patch proposals for safe refactorings. The system creates a separate branch, applies the smallest behavior-preserving transformation, runs the relevant tests, and produces a human-readable summary of what changed and why. Developers can accept the patch, edit it, or reject it with a reason. The feedback is then stored in the governance layer so that future recommendations become more repository-aware and less repetitive.

Model selection should be governed by data sensitivity, latency, cost, context length, and coding-language capability. Highly confidential repositories may require local models or private hosted endpoints, while lower-risk documentation or test-generation tasks may use managed services. ARC-TD is intentionally model-agnostic: the architecture can route review units to different models depending on task type, but the validation and governance layers remain constant so that model upgrades do not weaken controls.

Repository integration should be incremental and developer-centered. It can connect to GitHub, GitLab, Bitbucket, Azure DevOps, or internal code hosting services with persistent pull-request webhooks. It can also surface IDE hints for developers who only wish to preview before opening a PR. Both environments should follow the same evidence schema, which ensures early local feedback and formal review comments are consistent throughout the software delivery lifecycle.

Operational monitoring should track not only system uptime but also review value. Useful metrics include comment acceptance rate, suppressions, average evidence retrieval time, test-validation pass rate, patch rejection reasons, and post-merge incidents linked to reviewed code. These metrics should be reviewed with engineering leads, security teams, and platform owners so that ARC-TD evolves as an engineering control, not merely as an AI tool deployed for novelty.

The deployment blueprint concludes with a governance review board that periodically audits model behavior, policy thresholds, data handling, cost exposure, security posture, developer experience, and measurable quality outcomes. This board should include software architects, security representatives, senior developers, and product stakeholders. Its role is to decide which recommendations can become gates, which categories should remain advisory, and which repositories require specialized policies. Such oversight keeps autonomous review aligned with engineering judgment, developer autonomy, organizational accountability, and long-term software reliability.

10. GOVERNANCE, SECURITY, AND HUMAN OVERSIGHT

ARC-TD is designed for human-in-the-loop governance. The system should not approve pull requests independently; it should rank issues, explain evidence, suggest patches, and record reviewer decisions. Human reviewers remain responsible for architectural tradeoffs, product intent, regulatory interpretation, and risk acceptance. Probabilistic reasoning in multi-agent systems motivates this design because autonomous agents should represent uncertainty and coordinate with other decision actors rather than acting as unquestioned authorities [52].

Privacy is a central deployment concern. Enterprise code can contain proprietary logic, credentials, regulated workflows, and customer-specific behavior. ARC-TD supports local model deployment, prompt redaction, retrieval access controls, audit logging, and repository-level data boundaries. CI/CD risk-detection research in banking systems shows that automated pipelines must be governed with domain-specific controls, especially when review outputs can influence release approval [53].

Model feedback is incorporated through reviewer labels. When a developer dismisses a finding, the system asks for a lightweight reason: false positive, low priority, already handled, project convention, or invalid recommendation. These labels calibrate future thresholds and improve retrieval examples. End-to-end AI systems engineering research supports this closed-loop approach because lifecycle governance requires continuous learning from operational outcomes [54].

The framework also addresses platform-specific customization risk. In enterprise systems, an apparently useful AI recommendation can violate upgrade constraints, clean-core principles, or vendor-supported extension patterns. ARC-TD therefore stores platform policies and architectural decision records as retrieval artifacts. High-performance in-memory computing research on SAP S/4HANA highlights why platform-layer assumptions matter: performance and correctness depend on respecting architectural boundaries [55].

Auditability is maintained through immutable review records. Each automated finding includes the model version, prompt template, retrieval sources, static evidence, confidence score, validation results, reviewer action, and merge outcome. Dependency-graph modeling research for failure propagation reinforces this requirement because post-incident analysis often needs to reconstruct how a change moved through technical dependencies. ARC-TD therefore treats review metadata as operational evidence rather than disposable comment text [56].

11. DISCUSSION

The main advantage of ARC-TD is that it changes review automation from comment generation into decision augmentation. LLMs are strongest when synthesizing evidence, explaining tradeoffs, and proposing alternatives; they are weaker when asked to act without constraints. Automated root-cause and remediation research in multi-system data integrity contexts supports this distinction because corrective action must be connected to causal evidence, system dependencies, and validation gates [57].

Although ARC-TD is language-agnostic in principle, performance will differ by ecosystem. Languages with mature parsers, static analyzers, and testing frameworks will provide stronger evidence bundles than languages with weak tooling. Multimodal AI work in emotion and interaction is distant from code review, yet it illustrates a useful principle: intelligent systems should combine signals rather than depend on a single modality. ARC-TD similarly combines textual, structural, historical, and operational signals [58].

The system is most valuable in repositories where review load is high, domain risk is nontrivial, and code ownership is distributed. In such environments, automated summaries and validated recommendations can reduce reviewer fatigue and improve consistency. Real-time transaction validation research is relevant because critical systems require both rapid decision-making and high integrity. ARC-TD transfers this principle into pull-request governance by emphasizing fast but evidence-backed review decisions [59].

ARC-TD can also support modernization programs. When teams decompose monoliths, migrate platforms, or introduce new API layers, code review becomes a mechanism for enforcing architectural direction. The framework can detect whether new

changes reinforce or undermine the target architecture. Fault-aware microservice transition research supports this use case because migration quality depends on detecting coupling, gateway misuse, and service boundary instability before they become production failures [60].

Benchmarking remains a challenge. Repository-level software engineering tasks require long-context reasoning, execution environments, and realistic issue reconstruction. SWE-bench demonstrates that resolving real GitHub issues is substantially harder than isolated code generation, which supports the need for evaluation protocols that test review usefulness under realistic repository constraints. ARC-TD should therefore be benchmarked on pull-request histories, issue-linked fixes, and validated refactoring tasks rather than toy snippets [61].

12. THREATS TO VALIDITY AND LIMITATIONS

The first threat is construct validity. Technical debt, usefulness, and review quality can be measured in different ways, and developer acceptance does not always imply correctness. ARC-TD mitigates this risk by triangulating accepted comments, validation results, debt metrics, and post-merge outcomes. Explainable fraud-detection research offers a parallel: auditable decision pathways are needed when model outputs influence high-stakes operational decisions [62].

The second threat is external validity. Results from one organization, language, or review culture may not generalize to another. ARC-TD is therefore specified as a configurable framework with repository-specific thresholds, retrieval corpora, and policy controls. Converged AI architecture research for innovation and cybersecurity risk mitigation supports such configurability because enterprise AI systems must adapt to organizational context rather than impose uniform assumptions [63].

The third threat is automation bias. Developers may over-trust a polished LLM explanation or under-trust the system after a visible false positive. The framework mitigates this risk by displaying evidence, confidence, validation status, and human override options. CRM intelligence research in decentralized finance contexts shows that forecasting systems must be paired with customer and governance controls; similarly, code-review intelligence must be paired with reviewer authority and transparent limitations [64].

13. CONCLUSION

This paper proposed ARC-TD, a hybrid framework for autonomous code review using large language models, static analysis, retrieval, validation, and governance. The framework advances code review beyond generic AI-generated comments by grounding findings in repository evidence, validating refactoring proposals, and maintaining a technical-debt ledger that supports continuous quality improvement. The paper defined the architecture, scoring model, workflow, evaluation protocol, and human oversight controls required for enterprise deployment. Future work should implement ARC-TD across multi-language repositories, evaluate it against real pull-request histories, and measure long-term reductions in escaped defects and high-priority debt. Multi-cloud API architecture research reinforces the broader conclusion: modern software quality requires hybrid, context-aware, and platform-sensitive approaches that connect design, delivery, and operational reliability [65].

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