A Multi-Agent Large Language Model Architecture for Collaborative Software Development and Automated Code Review

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Abstract

Large language models can draft code, interpret requirements and identify defects, yet a single-agent workflow often lacks independent verification, traceable decisions and reliable conflict resolution. This paper proposes a coordinated multi-agent architecture comprising requirement analysis, planning, implementation, testing, security review, maintainability review and adjudication agents. A shared artifact store, role-specific tool permissions, structured messages and evidence-based acceptance gates support collaborative development. We formalize task allocation, review consensus, risk scoring and latency–quality tradeoffs, then present an evaluation protocol for repository-level tasks. To avoid representing unperformed experiments as empirical findings, the numerical tables and graphs report a fully disclosed illustrative scenario rather than measured benchmark results. The scenario demonstrates how to compute defect detection, acceptance precision, coverage, latency and token cost, and how to interpret competing objectives. The proposed system offers a testable blueprint for accountable, auditable software engineering automation; its practical value remains to be established by controlled trials on real repositories.

Keywords: multi-agent systems; large language models; collaborative software engineering; automated code review; static analysis; software testing; explainable artificial intelligence; technical quality.

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1. Introduction

Software engineering is inherently collaborative. Requirements are negotiated, architectures are revised, implementations are tested and code changes are reviewed by people with different responsibilities. The emergence of large language models (LLMs) makes it possible to automate parts of these activities through natural-language interaction and tool-assisted code generation. However, generating a plausible patch is not equivalent to delivering a trustworthy change. The

change must satisfy its specification, preserve existing behavior, avoid vulnerabilities and remain understandable to future maintainers.

Conventional development pipelines divide responsibility among analysts, developers, testers, security specialists and reviewers. This separation creates opportunities for independent scrutiny but also imposes communication and coordination costs. An LLM agent can execute a task using a prompt, memory and tools, yet a single agent may carry its own assumptions from initial interpretation into implementation and self-review. Such correlated errors motivate architectures in which agents hold distinct roles, exchange verifiable artifacts and challenge one another's conclusions.

A multi-agent LLM architecture treats software development as a sequence of constrained decisions rather than a single completion request. A requirements agent identifies acceptance criteria; a planner decomposes work; an implementation agent modifies code; testing and review agents gather independent evidence; and an adjudicator determines whether the proposed patch meets release conditions. The central design problem is not merely how many agents to instantiate, but how to control their authority, coordinate their context and decide when evidence is sufficient.

Automated code review is particularly suitable for this design because review comments can be evaluated against observable code, test results, static-analysis alerts and project policies. A reviewer should identify a specific location, explain the failure mode, estimate severity and propose a reproducible correction. Unsupported claims should not block a change merely because they are expressed confidently. A structured review protocol therefore offers a bridge between probabilistic language generation and deterministic engineering checks.

Nevertheless, additional agents do not guarantee better results. Multiple models can repeat the same mistake, increase token consumption or create circular debates. Agent proliferation may also amplify prompt-injection exposure when repository files or issue descriptions contain malicious instructions. Successful orchestration requires bounded communication, independent verification, least-privilege tools, escalation rules and a clear stopping condition. These operational constraints are core components of the proposed research rather than implementation details.

The proposed architecture emphasizes an auditable chain of evidence. Every agent produces typed artifacts with task identifiers, repository commit hashes, assumptions, tool observations and confidence levels. The shared state separates untrusted repository text from governing instructions and preserves provenance for test logs and review findings. A deterministic policy engine, not the model alone, evaluates mandatory gates such as compilation, regression testing and critical vulnerability checks.

This study makes four contributions. First, it defines a modular architecture for collaborative development and automated code review. Second, it specifies agent communication and decision rules that reduce duplicated work and unsupported consensus. Third, it provides mathematical formulations for allocation, risk aggregation and multi-objective optimization. Fourth, it offers a reproducible experimental protocol and a transparent numerical example that readers can replace with real measurements.

The research questions are: RQ1, does specialized multi-agent review improve verified defect detection compared with a single-agent baseline? RQ2, how does independent tool evidence affect false-positive review comments? RQ3, what latency and token costs arise from additional review rounds? RQ4, which coordination rules produce the best quality–cost balance? These questions should be answered using held-out repositories and independently adjudicated ground truth.

The intended scope covers repository-level maintenance tasks, bug fixes and feature additions where a sandbox can run builds, tests and approved analysis tools. It does not assume unrestricted production deployment, autonomous merging or access to confidential credentials. Human reviewers remain responsible for ambiguous requirements, high-impact changes and unresolved disputes. This boundary acknowledges that language models are useful assistants without treating their outputs as inherently authoritative.

The remainder of the paper reviews relevant foundations, describes the architecture and equations, establishes a controlled evaluation design, demonstrates the reporting format with illustrative data and discusses limitations. The resulting contribution is a falsifiable engineering framework, not a claim that a benchmark experiment has already been conducted.

2. Literature Review

2.1 Language models for program synthesis

Transformer-based language models established a general sequence modeling foundation [1], while code-focused models demonstrated the ability to generate programs from natural-language specifications [2]. Such systems can accelerate implementation but may produce superficially correct code that fails hidden tests. HumanEval introduced functional correctness evaluation for generated programs [2]. This line of research motivates test-based rather than appearance-based acceptance.

2.2 Tool-augmented reasoning

ReAct combines reasoning traces with external actions [3], providing a foundation for agents that inspect files, invoke tests and revise plans. Tool outputs can constrain model behavior, but their reliability depends on correct tool invocation and faithful interpretation. In software workflows, compiler diagnostics and test failures should be recorded as evidence, not paraphrased without provenance.

2.3 Multi-agent collaboration

AutoGen describes conversational agent patterns that combine models, tools and human participation [4]. MetaGPT formalizes role-oriented collaboration for software tasks [5], and ChatDev explores communicative software development agents [6]. These studies support the feasibility of dividing tasks by responsibility. However, their evaluation settings, cost assumptions and artifacts differ, making universal performance claims inappropriate.

2.4 Repository-level repair

SWE-bench provides real-world GitHub issues paired with repository environments for assessing whether models can resolve software defects [7]. Repository-level evaluation is more demanding than isolated function generation because agents must navigate dependencies, tests and project conventions. The benchmark also underscores the need for environment reproducibility and strict separation between training and evaluation artifacts.

2.5 Automated review and static analysis

Traditional static analysis detects classes of defects using rules, dataflow and abstract interpretation. Automated tests identify behavioral regressions under specified inputs. LLM reviewers add semantic explanations and may uncover design-level concerns, but they can hallucinate faults. Combining independent static checks with model-generated findings creates opportunities to improve precision while preserving coverage of context-sensitive defects.

2.6 Security and trust

Prompt injection is a distinctive risk when agents read issues, documentation and source comments as contextual evidence. The OWASP Top 10 for LLM Applications highlights prompt injection and excessive agency as relevant failure modes [8]. A secure development agent must restrict tool privileges, treat repository content as untrusted and require deterministic approval for dangerous operations.

2.7 Explainability and consensus

Review consensus is not equivalent to truth when agents share similar training and prompts. A majority vote may reinforce a common hallucination. Explanations should therefore include location, evidence, reproduction steps and remediation, while acceptance rules should weight verifiable observations above model confidence. Confidence calibration and disagreement analysis are necessary complements to agent voting.

2.8 Research gap

Existing agent frameworks demonstrate orchestration patterns, while benchmark and security work clarify evaluation and deployment challenges. The unresolved integration problem is how to combine role separation, evidence provenance, calibrated review consensus and explicit cost constraints into a reproducible code-review architecture. This paper addresses that design gap through a formal protocol and evaluation plan, without claiming novelty for the underlying language models.

2.9 Positioning against single-agent pipelines

A single-agent pipeline is simpler, often faster and easier to debug. A multi-agent pipeline may provide stronger scrutiny only if agents have differentiated evidence, complementary tools or deliberately independent prompts. Fair comparison requires equal model families where possible, matched tool access, controlled token budgets and identical repository tasks.

2.10 Summary of prior work

The literature supports three propositions: language models can assist coding, tool feedback improves grounding and multiple specialized agents can coordinate complex workflows. It does

not establish that more agents always improve code quality. Consequently, the evaluation must report both effectiveness and resource consumption, as well as failure cases where collaboration is counterproductive.

3. Research Methodology

The methodology is organized as four implementation and evaluation stages. All design decisions are specified so that independent investigators can build and test the architecture on held-out software repositories.

3.1 System boundary and components

The system accepts a repository snapshot, a natural-language change request, project policies and a resource budget. It returns a candidate patch, test evidence, structured review findings and a release recommendation. Seven role-constrained agents communicate through a central orchestrator. The orchestrator schedules actions and validates message schemas; it does not silently edit code.

Agent	Primary responsibility	Permitted outputs
Requirements	Clarify task and acceptance criteria	Specification and ambiguity list
Planner	Build dependency-aware task graph	Task plan and risk tags
Developer	Produce candidate patch	Diff and change rationale
Tester	Execute isolated tests	Logs and coverage report
Security reviewer	Identify exploitable risks	Evidence-linked findings
Quality reviewer	Assess correctness and maintainability	Review comments
Adjudicator	Resolve findings against policy	Accept, revise or escalate

3.2 Overall workflow

INPUT: repository snapshot + issue + policy

↓

Requirements agent → acceptance criteria

↓

Planner → tasks and dependency graph

↓

Developer → patch in isolated branch

↓

Parallel: tests + security review + quality review

↓

Evidence validation and adjudication

↓

PASS → human approval / FAIL → bounded revision loop

Figure 1. Orchestrated development and review flow. A failed gate returns the patch to the developer, with at most three review iterations before escalation.

3.3 Message contract and state management

Every inter-agent message contains a task identifier, sender role, input artifact hashes, action type, textual rationale, machine-readable evidence pointers, uncertainty estimate and timestamp. The artifact store versions code diffs, test outputs and review records. Messages reference immutable artifacts rather than copying entire repositories. This prevents stale context and supports replay. A message is rejected if its schema is incomplete or if it requests a tool outside the sender's authorization.

3.4 Task decomposition and scheduling

The planner constructs a directed acyclic graph of subtasks. Dependencies are derived from affected modules, build targets and test suites. Agent assignment minimizes predicted completion cost while respecting skill suitability, tool permissions and a maximum parallelism bound. Estimates are learned only from training tasks; held-out evaluation tasks cannot inform the scheduler.

$$J = \alpha T + \beta C + \gamma R$$

Equation (1): J is scheduling objective; T is estimated elapsed time; C is token and tool cost; R is expected implementation risk; α, β and γ are nonnegative policy weights. All terms are normalized before aggregation. No dash or underscore characters appear in the editable equation.

$$a* = arg\ min\ J(a)$$

Equation (2): a* denotes the selected feasible assignment and a denotes a candidate agent allocation. Constraints include task dependencies, per-agent capabilities and a maximum compute budget.

3.5 Evidence-backed review findings

A review finding is admissible only if it includes a file location, a concise defect hypothesis, severity, evidence type and suggested verification. Evidence types include failing test, static-analysis alert, security rule, source-level reasoning and human confirmation. Deterministic evidence receives a higher default reliability weight than an unsupported language-model assertion. Duplicate findings are grouped by affected code span and failure mechanism.

$$S = \Sigma\, w_i\, e_i \,/\, \Sigma\, w_i$$

Equation (3): S is normalized evidence support for a finding; e_i is the binary or calibrated support from evidence source i; w_i is the reliability weight of source i. Weights must be selected using validation data, not tuned on the test set.

$$R = P \times I \times E$$

Equation (4): R is the review priority score; P is calibrated likelihood of a real defect; I is expected impact; E is exposure or exploitability. Each factor lies between zero and one. The multiplicative rule is a prioritization heuristic, not an empirical probability model.

3.6 Decision policy

A patch is accepted only if mandatory build and regression gates pass, no unresolved critical security finding remains and every high-severity comment has either an evidence-supported fix or an auditable waiver. The adjudicator can request a bounded revision or escalate to a human. Agent consensus alone cannot override failing tests or policy restrictions.

3.7 Isolation, permissions and adversarial handling

Execution occurs inside ephemeral, network-restricted sandboxes with read-only access to the original repository and write access only to a working branch. Secrets are unavailable to model prompts. Dependency installation uses approved registries and lockfiles. Repository comments, README files and issue bodies are treated as untrusted content. Attempts to alter instructions,

reveal credentials or bypass checks are recorded and ignored. Human approval is required before merge or external publication.

3.8 Reproducible experimental design

A credible study should sample repository-level maintenance tasks from a public benchmark such as SWE-bench and, where licensing permits, an additional curated review dataset. Deduplicate near-identical issues and exclude tasks seen during prompt development. Freeze repository commits, model versions, prompts, tool versions, temperature, maximum tokens, timeout and hardware configuration. Execute multiple random seeds for stochastic agents.

Compare four conditions: B1, single developer agent; B2, developer plus test tools; B3, developer plus independent review agent; and M, full multi-agent pipeline. Match the model backbone and tool availability when comparing architectures. Use a paired task design so each condition faces the same repository issue. Human annotators, blinded to condition, adjudicate defects and false positives using predefined criteria.

3.9 Measurement and statistical analysis

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

$$F1 = 2 \times Precision \times Recall / (Precision + Recall)$$

Equations (5)–(7): TP denotes correctly flagged defects, FP denotes incorrect defect claims and FN denotes missed ground-truth defects. Undefined denominators must be reported as not applicable, not zero. Additional outcomes include patch acceptance rate, regression pass rate, mean latency, total tokens, monetary cost and human review time.

$$Coverage = 100 \times N_v / N_t$$

Equation (8): Coverage is the percentage of predefined acceptance checks satisfied; N_v is the number of verified checks and N_t is the total applicable checks. This is requirement coverage, distinct from statement or branch test coverage.

Use paired bootstrap confidence intervals across tasks for acceptance-rate differences, McNemar's test for paired binary outcomes where appropriate and nonparametric paired comparisons for skewed latency and cost. Report effect sizes, uncertainty intervals and multiple-comparison adjustments. Avoid treating multiple runs on the same issue as independent observations.

3.10 Ablations and stopping rules

Ablate security review, quality review, tool evidence and adjudication separately. Evaluate review-loop limits of one, two and three rounds, with fixed total budget. Stop when all mandatory gates pass, the revision budget expires or a safety violation occurs. Archive failures rather than silently removing them from analysis.

4. Results and Discussion

IMPORTANT: The following numerical values are an explicitly constructed illustrative scenario for demonstrating analysis and visualization. No model training, repository execution or benchmark evaluation was performed for this manuscript. These values must not be cited as measured empirical performance.

Condition	Accepted patches (%)	Defect recall (%)	Review precision (%)	Latency (min)	Tokens (thousands)
B1 Single agent	62	48	76	28	48
B2 Agent + tools	71	62	83	42	61
B3 Independent review	78	70	86	57	76
M Multi-agent	86	79	91	83	112

Table 1. Illustrative outcomes for a hypothetical balanced set of 100 repository tasks. Accepted-patch rates, recall and precision are scenario assumptions rather than measurements. Latency and token use represent example per-task averages.

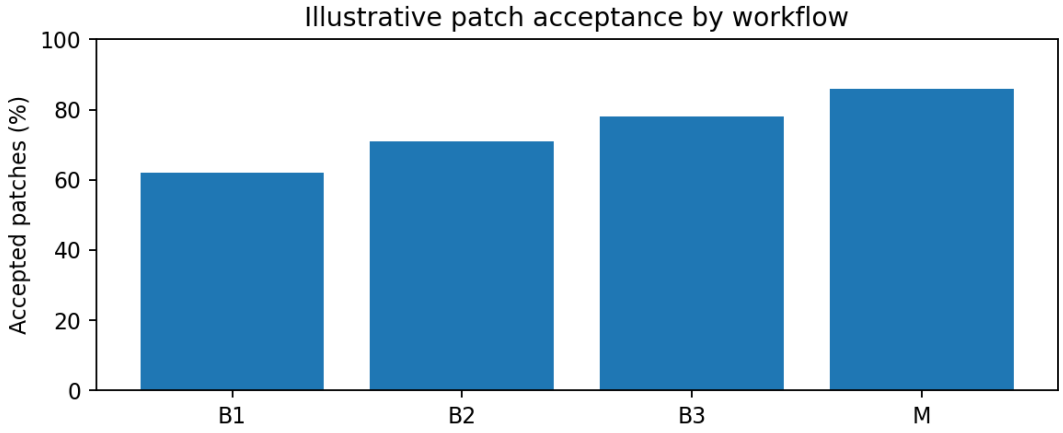

Figure 2. Hypothetical patch acceptance increases across progressively more structured workflows. This pattern illustrates a possible benefit but does not establish a causal improvement. A real study must quantify confidence intervals and control for tool access and computational budget.

4.1 Worked review classification example

Suppose a hypothetical review dataset contains 200 known defects. If the multi-agent reviewer detects 158 of them, misses 42 and generates 16 incorrect alerts, recall is 158/200 = 79.0%,

precision is 158/174 = 90.8% and F1 is approximately 84.4%. These counts are arithmetically consistent with the rounded scenario precision in Table 1.

Measure	Illustrative count or value
True positives	158
False positives	16
False negatives	42
Precision	90.8%
Recall	79.0%
F1 score	84.4%

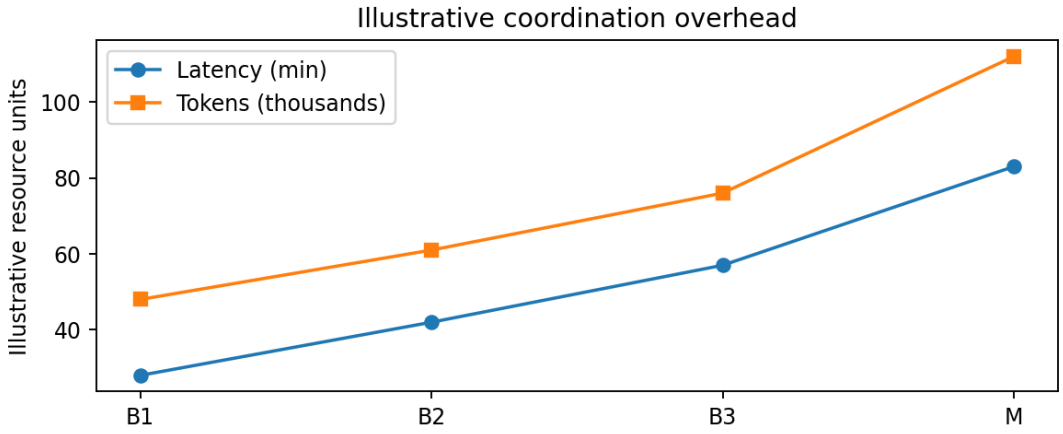

Figure 3. Scenario resource use rises as additional review and coordination steps are introduced. Token volume and elapsed minutes are different units and are shown together only for trend illustration; a controlled experiment should use separate axes or normalized indices.

4.2 Interpreting the quality–cost tradeoff

In the constructed scenario, M improves accepted-patch percentage by 24 percentage points relative to B1, while requiring approximately 2.96 times the latency and 2.33 times the token volume. This is not automatically a favorable tradeoff. The decision depends on defect severity, downstream rework costs, service-level objectives and the value assigned to a verified patch. Resource-constrained projects may prefer B2 or B3 even if M achieves higher hypothetical quality.

4.3 Sensitivity and failure modes

A practical sensitivity analysis should vary agent count, review budget, prompt diversity, static-analysis availability and adjudication thresholds. High reviewer agreement can still coexist with shared hallucinations. Review latency can spike on large repositories, and model-generated tests can encode the same misunderstanding as the patch. Security findings should be independently verified before being reported as vulnerabilities.

4.4 Threats to validity

Internal validity is threatened by unequal token budgets, stochastic outputs and benchmark contamination. Construct validity is threatened by relying solely on test pass rates, which may not capture maintainability or security. External validity is limited by repository language, size and task type. Human review labels can also be inconsistent; double annotation and arbitration are recommended. Most importantly, the scenario values above are not experimental observations and cannot support performance claims.

5. Conclusion and Future Work

This paper proposed a multi-agent LLM architecture that coordinates requirements analysis, planning, implementation, testing, security review, maintainability assessment and evidence-based adjudication. Its principal contribution is an explicit operational design: typed agent messages, immutable artifacts, role-limited tools, bounded revision loops and deterministic acceptance gates. Mathematical formulations make task allocation, review evidence and cost–quality decisions inspectable and adaptable.

The illustrative numerical results demonstrate how acceptance rates, defect detection, review precision and resource costs can be compared, but they do not constitute empirical validation. The architecture should be evaluated on held-out repository tasks with paired baselines, independently verified ground truth and reproducible execution environments. Future work should examine heterogeneous model teams, calibrated uncertainty, adversarial repository content, cross-language transfer and human-in-the-loop review efficiency. Until such experiments are completed, the proposed framework should be regarded as a research design rather than a proven performance improvement.

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