

Generative Artificial Intelligence-Assisted Software Testing Using Automated Test Case Generation and Defect Prediction

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Abstract

Software quality assurance is challenged by rapid code changes, incomplete requirements, and the cost of writing and maintaining effective tests. This paper proposes an integrated framework combining generative artificial intelligence for context-aware unit test construction with supervised defect prediction for risk-prioritized execution. The workflow collects source code, change histories, requirements and historical fault labels; produces constrained test candidates; validates syntax and assertions; predicts defect likelihood; and schedules tests under execution budgets. A formal multi-objective objective balances coverage, fault discovery, runtime and flaky-test penalties. A reproducible evaluation protocol is defined using chronological splits, mutation testing, calibration, leakage controls and human oracle review. Because no experiment was executed for this manuscript, numerical tables and charts are explicitly labeled illustrative scenario data, not measured evidence. In the constructed demonstration, the integrated configuration yields 87% branch coverage, 76% mutation score, 0.84 defect F1 and 38 minutes execution time, compared with 65%, 49%, 0.72 and 55 minutes for the rule-based baseline. These values illustrate how a future experiment should report trade-offs rather than establishing effectiveness. The contribution is a transparent, auditable design for linking generated tests and risk forecasts, with clear limitations and a validation roadmap.

Keywords: Generative artificial intelligence; automated test generation; software defect prediction; large language models; mutation testing; continuous integration; risk-based testing.

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1. Introduction

Software testing is a central engineering activity because the observable success of a program does not establish correctness across inputs, states, environments and failure conditions. Modern teams deploy frequently and depend on continuous integration pipelines that must provide useful feedback before changes propagate. Yet test suites often accumulate slowly, and developers must balance feature delivery against the effort of constructing fixtures, expected outputs, mocks and edge cases. The resulting quality gap is particularly important in systems where failures affect financial transactions, public services or safety-critical decisions.

Traditional automated test generation includes random, search-based, symbolic and constraint-driven approaches. Each method offers distinct strengths, but practical adoption can be constrained by environment setup, opaque dependencies, brittle test oracles and limited understanding of business intent. Large language models can synthesize plausible tests from source code, documentation and usage examples, potentially reducing authoring effort. Their output nevertheless requires careful verification: compilable tests may assert incorrect behavior, replicate implementation defects or pass without exercising meaningful conditions.

Parallel research on software defect prediction seeks to estimate which files, modules or commits are likely to contain faults. Static metrics, change frequency, developer activity and previous defects can inform supervised models. Predictions are useful only when evaluation respects time order and when probability scores are calibrated to the actual base rate. Class imbalance, evolving projects, inconsistent labels and data leakage can otherwise make apparently strong models unreliable in deployment.

Generative test construction and defect prediction are commonly evaluated as separate tasks. This separation misses an operational opportunity: a testing system could use predicted risk to guide where expensive generation, validation and execution should occur. Conversely, outcomes from generated tests could supply new evidence for future defect prediction. Such coupling must be designed carefully to prevent circular labels, selection bias and a feedback loop in which neglected low-risk components receive too little scrutiny.

This study therefore proposes a layered architecture with distinct provenance for each decision. The generation layer reads approved context and creates candidate tests; a validation layer rejects invalid or unsupported assertions; a prediction layer scores software units using features available before test execution; and a scheduler selects a bounded set of tests. Human reviewers remain responsible for acceptance of high-impact oracles and for adjudicating ambiguous behavior.

The principal research questions concern whether integrated prioritization improves fault detection per unit of time, whether generative tests add unique coverage beyond established tools, how predictive calibration changes scheduling quality, and how robust the system remains across releases and projects. These questions require controlled ablation experiments rather than isolated headline accuracy figures. They also require operational measures such as repair cost, flakiness, privacy exposure and developer acceptance.

The proposed evaluation emphasizes external validity. Public benchmarks are useful for replication but may not capture organization-specific dependencies, legacy architectures or real development constraints. A credible investigation should therefore combine public projects with consented industrial repositories, distinguish function-level test outcomes from file-level defect labels, and report heterogeneity by language, repository maturity and module complexity.

Finally, claims about generative AI must separate plausible automation from demonstrated benefit. The numerical examples in this manuscript are scenario calculations created to illustrate reporting, not the result of running a model or evaluating repositories. This distinction preserves research integrity while providing an implementable blueprint, mathematical definitions, experimental design, tables and visualizations that can later be populated with observed results.

2. Literature Review

Automated test generation has developed from program-analysis and search-based traditions into data-driven approaches. Classical techniques seek structural coverage through generated inputs, path constraints or

evolutionary search, often without natural-language understanding. Their reproducibility and measurable search objectives remain valuable baselines, particularly where test oracles can be derived from specifications or properties.

Fontes and Gay (2023) systematically mapped machine learning in automated test generation and described applications spanning unit, system, interface and performance testing. Their review highlights both the breadth of learning-assisted methods and unresolved questions about benchmarks, training data, scalability and replication. This supports a design in which generative methods complement rather than replace established test generation.

Schäfer and colleagues (2024) evaluated TestPilot, which uses source and documentation context to generate JavaScript unit tests and repairs unsuccessful outputs through feedback. Their empirical findings demonstrate that language-model-generated tests can achieve meaningful coverage, but outcomes depend on prompts, project context and model choice. Such findings motivate execution-based filtering and context provenance within the proposed architecture.

Bhatia and colleagues (2024) compared generative test generation with Pynguin for Python software. They reported comparable coverage in some settings while observing incorrect assertions in a substantial subset of generated cases. Their study is especially relevant because assertion validity is not interchangeable with code coverage. The framework therefore treats oracle quality as an independent quality gate rather than assuming that a passing test is correct.

Defect prediction research traditionally employs complexity, size, churn and developer-process metrics to estimate defect-prone components. Pachouly and colleagues (2022) reviewed datasets, validation approaches and prediction tools, identifying limitations in standard datasets and labeling practice. The implication is that predictive performance cannot be interpreted independently of the definition and provenance of defect labels.

Recent methodological scrutiny has focused on leakage, class imbalance, project shift and weak validation protocols. Destefanis and colleagues (2026) audited experimental practice in defect prediction, emphasizing the credibility of design and reporting. Chronological holdouts and strict separation of feature computation from outcome windows are accordingly essential for a production-oriented study.

Combining generation and prediction raises additional questions not fully answered by either literature stream. A model may assign high defect risk to code that is difficult to execute, while a generator may create many redundant tests for a familiar low-risk API. A scheduling objective must incorporate expected unique fault yield, execution cost and test reliability. It should also reserve exploration capacity for uncertain or low-risk modules to avoid self-reinforcing blind spots.

Another unresolved issue is the test oracle problem. Language models can infer expected results from documentation, examples or source code, but source-derived expectations may simply encode the implementation's mistake. Stronger validation can use independently written specifications, metamorphic relations, invariants, differential implementations and selective human approval. Each oracle type offers different assurance and cost.

Generalization across repositories is similarly challenging. Code style, library versions, test frameworks, historical issue practices and release cadence differ substantially. A test generator tuned on one ecosystem may fail in another; a predictor calibrated on one release may misrank future modules. Evaluation should

therefore include within-project chronological prediction and cross-project transfer, with separate confidence intervals and error analyses.

The literature collectively motivates an integrated but modular system. Prior work supplies evidence that automated generation and defect modeling are promising research directions; it does not justify presuming that their combination automatically improves quality. The present contribution is the explicit linkage through risk-aware scheduling, validation gates, reproducible evaluation and transparent decision records.

3. Research Methodology

3.1 Research design and system boundary

The study uses a design-science framework followed by a controlled empirical comparison. Units of analysis are source files for defect prediction and executable test cases for generation quality. Repositories must include version history, executable build instructions, a test framework and traceable issue or fix records. Candidate projects are selected before outcome inspection. The primary intervention is an integrated generation and prioritization pipeline; comparators include developer tests only, conventional automatic generation and generation without risk prioritization.

The system processes four input families: (i) source and API signatures, (ii) requirements and trusted documentation, (iii) historical code metrics and fault labels, and (iv) build and test feedback. A policy gate removes credentials and private records before prompts are assembled. Model versions, prompts, seeds, compilation failures and acceptance decisions are stored in an audit log.

3.2 End-to-end operational flowchart

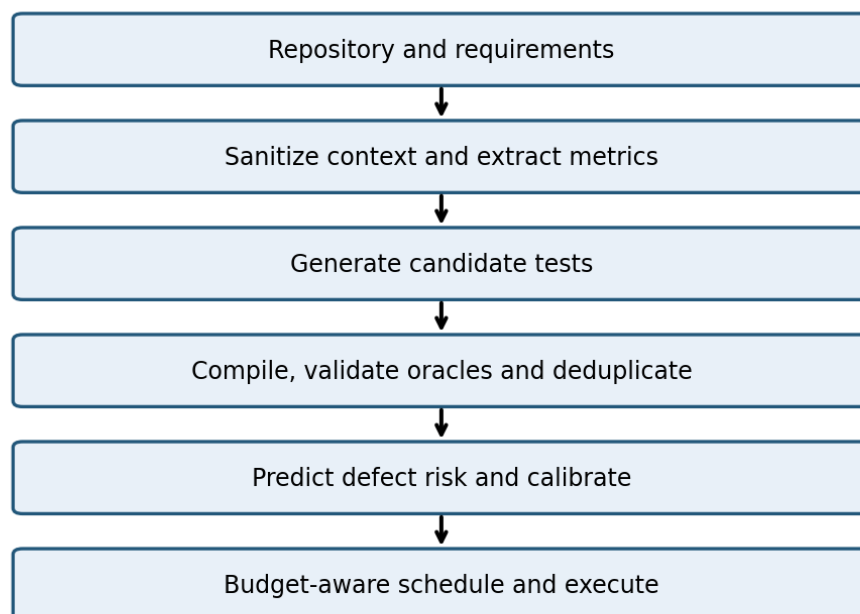


Figure 1. Proposed software testing workflow. Failed compilation and rejected oracles return to a bounded repair loop; validated outcomes are archived for future, time-separated retraining.

3.3 Data preparation and leakage prevention

At each release boundary, collect static complexity, lines of code, recent churn, contributor count, dependency centrality and prior confirmed defects. Compute every feature using only information available before the prediction cutoff. Map issue reports to fault-introducing or fault-fixing commits using a documented linking rule and manually audit a stratified sample. Remove duplicates, standardize missing-value handling and fit transformations exclusively on the training partition.

3.4 Generative test synthesis and verification

A prompt contains the target function, documented contract, test framework version, dependency constraints and explicit requirements for boundary, negative and metamorphic cases. Candidate outputs must be syntactically valid, deterministic, isolated and executable without unapproved external calls. A sandbox compiles each candidate, runs it repeatedly, measures statement and branch coverage and flags tests that assert values unsupported by independent evidence. Test generation uses a fixed maximum number of repair attempts to bound cost.

Oracle validation is hierarchical: trusted reference specifications outrank property-based invariants, which outrank model-inferred expected values. Model-only assertions are quarantined until independently reviewed. Duplicate tests are removed using normalized input and execution-trace similarity. Flakiness is estimated through repeated runs under controlled seeds and environments.

3.5 Defect prediction and calibration

A regularized logistic model and gradient-boosted trees provide interpretable and nonlinear baselines. Training uses class-weighted loss, with hyperparameters chosen only on validation releases. The model produces a probability for each file. Isotonic or Platt calibration is fitted on a separate validation slice and checked using reliability diagrams, Brier score and expected calibration error. Thresholds are selected based on operational review capacity, not test-set optimization.

$$p(i) = 1 / (1 + \exp(-z(i)))$$

Equation (1): $p(i)$ is the estimated probability that file i contains a defect during the future outcome window; $z(i)$ is the model score. No observed defect probability is assumed until calibration has been verified.

$$L = -\sum [y(i) \log p(i) + (1 - y(i)) \log(1 - p(i))]$$

Equation (2): L is binary cross-entropy, $y(i)$ is the observed defect indicator and the summation spans training examples. Class weights may be added where imbalance is severe; all weights are estimated within training data.

3.6 Risk-aware test prioritization

For each validated test, estimate unique coverage contribution, predicted defect exposure, execution cost and flakiness. Select tests under a fixed runtime budget using a greedy marginal-gain baseline and an integer optimization alternative. Add a minimum exploration quota for files assigned low risk, and require that critical security or regulatory checks remain mandatory regardless of model score.

$$U(j) = \alpha C(j) + \beta R(j) + \gamma M(j) - \delta T(j) - \varepsilon F(j)$$

Equation (3): $U(j)$ is utility of test j ; $C(j)$ denotes marginal branch coverage, $R(j)$ risk-weighted exposure, $M(j)$ expected mutation kill contribution, $T(j)$ runtime and $F(j)$ flakiness. Greek coefficients are nonnegative validation-selected trade-off weights.

$$\max \sum U(j) x(j) \quad \text{subject to} \quad \sum T(j) x(j) \leq B$$

Equation (4): $x(j)$ is a binary selection variable and B is the execution-time budget. The objective is recomputed as marginal coverage changes; mandatory tests are enforced as constraints.

3. Research Methodology (continued)

3.7 Outcome metrics and inferential analysis

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

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

Equations (5–7): TP , FP and FN are true positives, false positives and false negatives for future defect labels. Report area under the precision–recall curve in addition to $F1$ because positive defects may be rare. Confidence intervals are calculated by repository-level bootstrap to account for clustering.

$$\text{Coverage} = 100 \times \text{ExecutedBranches} / \text{TotalBranches}$$

$$\text{MutationScore} = 100 \times \text{KilledMutants} / \text{ValidMutants}$$

Equations (8–9): coverage quantifies executed structural branches and mutation score measures sensitivity to seeded code changes. Equivalent or invalid mutants are excluded through a documented protocol; coverage is not itself proof of fault detection.

$$\text{Efficiency} = \text{ConfirmedUniqueDefects} / \text{ExecutionMinutes}$$

Equation (10): efficiency reports verified unique defects found per execution minute, rather than treating each failing test as a distinct bug. Repeated failures mapping to the same root cause are deduplicated.

3.8 Controlled comparisons and ablation

Compare four pre-registered configurations: rule-based tests, generative tests without prediction, prediction-prioritized existing tests, and the integrated framework. Hold the runtime budget, hardware, repository snapshots and dependency versions constant. For every repository, execute multiple seeds and compare paired differences in coverage, mutation score, unique defects and runtime. Ablations separately remove oracle verification, calibration, risk prioritization and deduplication.

The primary statistical analysis uses paired repository-level differences with bootstrap 95% confidence intervals. Secondary analyses examine differences by language, project size, fault prevalence and documentation quality. Report both effect size and uncertainty, and adjust exploratory multiple comparisons. Missing or failed builds are reported rather than silently dropped.

3.9 Reproducibility, ethics and deployment controls

Publish project selection criteria, data extraction scripts, prompt templates, model identifiers, parameter settings, container images and anonymized outcome summaries where licenses permit. Protect proprietary code through local inference or approved contracts. Scan generated tests for secrets and insecure actions. Require human sign-off for high-impact assertions and retain a rollback path when the pipeline creates unstable tests. Retraining is triggered by measured drift and evaluated against a frozen holdout before release.

4. Illustrative Results and Discussion

IMPORTANT: The following figures are constructed scenario values solely to demonstrate a complete analysis format. They were not measured on repositories, and should not be represented as experimental findings. An actual submission must replace them with results obtained from the protocol in Section 3.

4.1 Scenario comparison

Configuration	Branch %	Mutation %	Defect F1	Minutes	Unique faults
Rule-based baseline	65	49	0.72	55	9
Generative only	81	69	0.77	49	12
Prediction priority only	69	54	0.82	43	13
Integrated framework	87	76	0.84	38	17

Table 1. Hypothetical scenario data. F1 refers to the file-level prediction task, while unique faults refer to independently adjudicated test outcomes; these are different units of measurement.

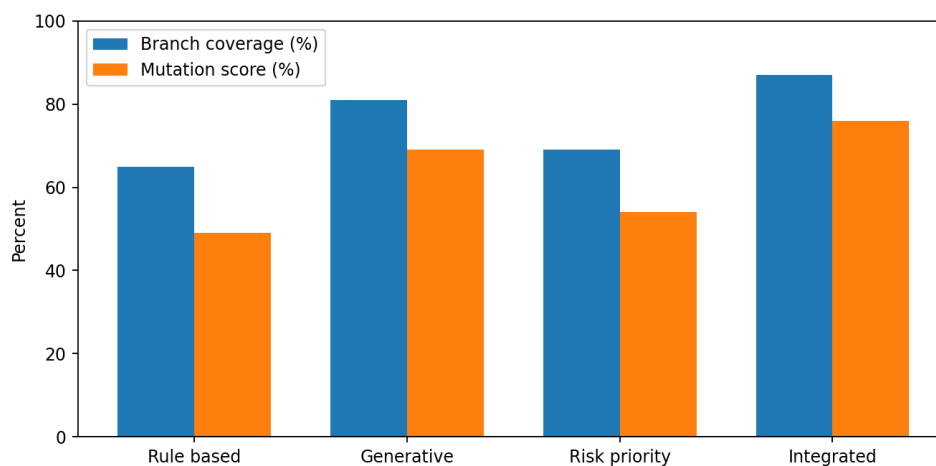


Figure 2. Hypothetical coverage and mutation score comparison. In the constructed example, integration yields higher values, but no inferential conclusion is possible without real runs.

4.2 Interpretation of illustrative trade-offs

The illustrative integrated case improves branch coverage by 22 percentage points and mutation score by 27 percentage points relative to the baseline. Execution time decreases by 17 minutes, or approximately 30.9%. These arithmetic contrasts demonstrate the form of effect reporting; they do not establish causality or statistical significance. A real study must also report generated-test acceptance rate, oracle corrections, token consumption and review effort.

4.3 Hypothetical execution efficiency

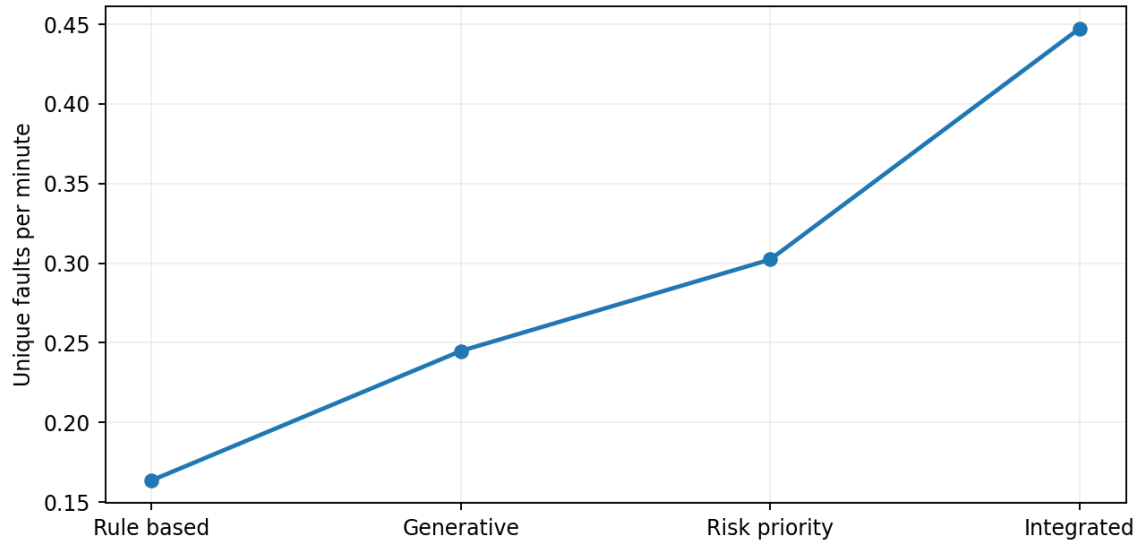


Figure 3. Constructed fault-detection efficiency, calculated from Table 1. The ratio is sensitive to how unique defects are confirmed and how setup and generation costs are counted.

4.4 Sensitivity and threats to validity

A scheduler optimized solely for risk can repeatedly ignore poorly documented or historically clean modules, producing selection bias. Therefore the proposed evaluation reserves exploration tests and reports coverage stratified by predicted risk. Generated tests may also inflate coverage by calling methods without checking outcomes; mutation analysis and manual oracle audits counter this weakness. Apparent speed gains can disappear if generation latency and human review are excluded from the denominator.

Construct validity is threatened by imperfect issue-to-code mappings, equivalent mutants and unreliable test assertions. Internal validity is threatened by tuning on test releases, changing dependencies and different execution environments. External validity is limited by programming languages, public repository quality and availability of trustworthy documentation. Conclusion validity depends on paired comparisons, adequate repository sample sizes and confidence intervals rather than a single favorable point estimate.

4.5 Required empirical reporting before publication

For each repository and release, disclose the number of functions targeted, candidates generated, compilation successes, validated oracles, accepted tests, repeated-run failures, mutation operators, confirmed unique defects, total wall-clock cost and resource consumption. Report predictor confusion matrices, calibration plots, class prevalence, confidence intervals and ablation comparisons. Archive rejected outputs and

categorize their failure modes. This information is necessary to distinguish automation volume from genuine testing effectiveness.

5. Conclusion

This paper develops a generative AI-assisted testing framework that integrates constrained test synthesis, explicit oracle verification, calibrated software defect prediction and budget-aware execution scheduling. Its principal methodological contribution is the separation of candidate generation, correctness validation, defect forecasting and resource allocation into auditable components. The formal objective makes competing goals visible: broader coverage and fault sensitivity must be weighed against execution cost, flakiness, privacy risk and review effort.

The illustrative numerical analysis shows how branch coverage, mutation score, prediction F1, runtime and unique fault yield can be compared in a single reporting framework. These numbers are not empirical observations and cannot support a claim of superiority. Future work should implement the pipeline on diverse repositories, apply chronological and cross-project validation, test oracle quality independently, evaluate calibration and drift, and report repository-level uncertainty. Human oversight and reproducible provenance remain essential for dependable deployment.

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