

An Explainable Machine Learning Framework for Software Reliability Prediction and Automated Technical Debt Assessment

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Abstract

Software reliability forecasting and technical debt management are frequently treated as separate engineering decisions despite sharing code quality, change history, architecture and operational context. This paper develops an explainable machine learning framework that jointly estimates defect-proneness and future incident risk while producing a traceable technical debt priority score. The proposed pipeline integrates repository commits, issue records, static analysis measures, test coverage, dependency topology and deployment telemetry; enforces time-aware validation; calibrates risk estimates; and uses SHAP-style feature attributions with counterfactual checks. A cost-aware ranking combines expected reliability loss, estimated remediation effort, interest accumulation and uncertainty. A synthetic worked example illustrates the reporting protocol, including discrimination, calibration, debt prioritization and ablation. These numerical results are demonstrative, not empirical claims. The framework emphasizes data provenance, human review, model drift and reproducible evaluation, enabling engineering teams to connect model explanations to actionable maintenance decisions.

Keywords: explainable artificial intelligence; software reliability; technical debt; defect prediction; model calibration; SHAP; maintenance prioritization; software analytics.

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1. Introduction

Software-intensive organizations must balance delivery speed against the cumulative consequences of defects, brittle dependencies, inadequate testing and architectural shortcuts. Reliability refers to the probability that a system performs its intended functions without failure over a specified operating period and context. Technical debt, by contrast, describes future costs introduced by expedient design or implementation decisions. The concepts are related but not interchangeable: a codebase can contain substantial debt without

immediate failures, while a newly introduced defect can produce severe operational consequences despite low measured debt.

Traditional reliability models often depend on failure histories and assumptions about defect discovery processes. Modern software environments complicate those assumptions because deployments are continuous, services are distributed, workloads shift and code is repeatedly modified. Repository and operational telemetry offer richer predictors, including change frequency, code churn, complexity, developer ownership, test coverage, dependency centrality, incident counts and service-level indicators. Nevertheless, correlation alone is insufficient for directing engineering investment.

Machine learning can identify nonlinear relationships between software metrics and observed incidents. Tree ensembles are particularly attractive for heterogeneous tabular features, whereas temporal neural models may help with event sequences. Yet a high-performing classifier can be unhelpful if its probabilities are miscalibrated, its predictions leak future information or its explanations highlight proxies that teams cannot change. A practical framework therefore requires reliability-aware labeling, temporal validation, interpretable outputs and explicit decision rules.

Technical debt assessment also requires careful operationalization. Static analysis findings are useful but incomplete: maintainability warnings may overstate trivial style issues and miss costly architectural coupling. A single aggregated debt score obscures differences among principal remediation effort, recurring interest, risk of incident and business impact. An automated assessment should preserve component-level evidence, uncertainty and engineering judgment rather than claiming to compute an objective monetary truth.

This research proposes a unified pipeline that estimates near-term defect or incident likelihood and converts calibrated risk into a transparent debt remediation ranking. It combines static and dynamic evidence while separating predictive features from decision weights. Reliability forecasts answer what might fail; debt analysis asks what should be fixed first given available capacity and expected benefit. This distinction is crucial when low-risk code has large maintainability costs or high-risk services are too expensive to refactor immediately.

The proposed contribution is methodological rather than a claim of novel benchmark superiority. First, the paper specifies a common data model linking commits, modules, defects and incidents with explicit observation and prediction windows. Second, it introduces an explainability layer combining global feature importance, local attributions and actionable counterfactual scenarios. Third, it defines a cost-aware prioritization objective that includes expected failure loss, debt interest and remediation effort. Fourth, it specifies validation checks designed to expose temporal leakage, group disparities, calibration error and operational drift.

The unit of analysis is a software component observed at a release or monthly checkpoint. Predictors are frozen at the checkpoint, and outcomes are measured in a subsequent horizon. This simple separation prevents a common source of optimistic results: incorporating post-release defect fixes, retrospective issue labels or future test changes into training features. Component identity, version and timestamp are retained for auditing while potentially identifying developer attributes are excluded from deployment decisions.

Interpretability is approached as evidence rather than proof of causation. SHAP-like local contributions can explain why a model assigned a higher probability relative to its background distribution, but correlated metrics can divide attribution in unstable ways. Counterfactual experiments, such as simulating a reduction in dependency cycles, should be described as model-based scenarios rather than guaranteed causal improvements. Experts must verify whether suggested changes are technically feasible.

For evaluation, the paper recommends discrimination metrics such as area under the receiver operating characteristic curve and precision-recall area, together with Brier score, expected calibration error and recall at fixed review capacity. Ranking quality is assessed using the proportion of observed high-impact defects captured among the top-priority components and realized cost reduction in a prospective pilot. Bootstrap confidence intervals and project-level holdout tests are necessary before any substantive performance claim.

The remainder of the paper reviews foundational research, develops the end-to-end methodology, presents an explicitly synthetic numerical example and discusses validity threats. The aim is to provide a reproducible blueprint for an explainable software quality decision-support system that assists engineers without replacing their accountability.

2. Literature Review

Software reliability engineering has a long history of probabilistic modeling. Musa, Iannino and Okumoto formalized approaches to estimating failure behavior from execution and defect data, while later work emphasized the dependence of predictions on operating conditions and data quality. Classical models are useful for understanding failure processes but may be less suitable when service architectures, release practices and workloads change rapidly.

Empirical software defect prediction studies established that static code and process measures can support predictive classification. Menzies, Greenwald and Frank reported lessons from learning defect predictors using static attributes, illustrating both the potential of data-driven prediction and the importance of dataset context. Subsequent research has questioned cross-project generalization and warned that apparent benchmark improvements may be fragile.

Lessmann and colleagues compared classification models for defect prediction and argued for more careful benchmarking. Their work is important because many algorithms yield similar performance once evaluation conditions are controlled. This motivates reporting uncertainty and practical decision utility rather than declaring a universally superior learning algorithm.

Process metrics often add useful information beyond code metrics. Historical churn, recent edits and ownership dispersion reflect change dynamics that static snapshots may miss. However, these variables can act as proxies for component size or team structure, so models should normalize exposure and inspect subgroup errors. A large, frequently modified module may attract more bug reports simply because it receives more attention.

Technical debt was introduced by Cunningham as a metaphor for the future consequences of expedient software decisions. Later literature distinguished debt principal from interest and expanded the concept to

architectural, design, test, documentation and infrastructure debt. Li, Avgeriou and Liang systematically mapped technical debt research, identifying management and measurement as persistent challenges.

Static analyzers such as SonarQube provide rule-based maintainability indicators and estimated remediation times. These estimates can aid triage, but they should not be interpreted as measured business losses. Debt registers, architecture reviews and dependency analyses capture context that automated rules omit. Accordingly, the proposed framework uses analyzer outputs as inputs rather than treating them as ground truth.

Explainable artificial intelligence provides tools for interrogating model behavior. Lundberg and Lee introduced SHAP as a unified framework for additive feature attribution. SHAP can provide consistent local explanations under specified assumptions, but feature dependence, background sample choice and model instability complicate interpretation. Explanations must therefore be accompanied by provenance and sensitivity analysis.

Ribeiro, Singh and Guestrin proposed LIME for local surrogate explanations. LIME offers a model-agnostic approach but its explanations may vary with perturbation sampling and neighborhood definition. For software metrics with strong constraints, unrealistic perturbations can create misleading recommendations. This paper favors constrained what-if analysis and explicit separation between explanatory and actionable variables.

Probability calibration is essential when model scores drive expected-cost calculations. Niculescu-Mizil and Caruana showed that supervised learners can differ substantially in probability quality. Platt scaling and isotonic regression can improve calibration when fitted only on a held-out calibration set. AUC alone is insufficient when the decision system multiplies predicted probability by financial or operational impact.

Prior research also highlights reproducibility problems in software analytics: inconsistent labeling, duplicate components, leakage across releases and unreported class prevalence can distort findings. The present design therefore defines a temporal protocol, records preprocessing transformations and recommends project-wise external validation. It treats fairness across repositories and services, data minimization and human override as operational requirements rather than optional extensions.

3. Research Methodology

3.1 Research design and unit of analysis. The framework uses a retrospective longitudinal cohort of component checkpoints, followed by a prospective shadow-mode evaluation. Each observation represents a module or service at time t . The feature window covers the preceding 90 days; the prediction horizon covers the following 30 days. These windows are configurable but must be fixed before testing. The primary outcome is whether at least one verified, component-attributed production incident or severity-weighted defect occurs in the prediction horizon. The secondary outcome is future maintenance effort measured from accepted work items, where available.

3.2 Data collection and linkage. Extract repository history, pull-request metadata, issue tracker events, continuous-integration test reports, static analyzer findings, dependency graphs and incident records. Normalize component identifiers across renames and repository moves. Link incidents to affected versions

using deployment manifests and root-cause records; ambiguous links receive an unknown label rather than forced attribution. Remove personally identifying developer information, retain only aggregate ownership concentration and document consent and retention rules.

3.3 Feature engineering. Candidate predictors include log code size, cyclomatic complexity, duplication percentage, churn per thousand lines, change frequency, review latency, test coverage, flaky-test rate, open critical findings, dependency fan-in, graph centrality, historical incident frequency and service criticality. Compute all values using only events available at the checkpoint. Missingness indicators are retained, skewed counts are log transformed, and categorical repository or language information is encoded without revealing future outcomes.

3.4 Ground truth and splits. Incidents are deduplicated by root cause and severity; reopened issues are not double counted. Reserve the latest contiguous time block as test data, earlier blocks for training and a separate intermediate block for calibration. Introduce a temporal gap when incident adjudication can be delayed. Group related component versions to reduce near-duplicate contamination. Evaluate a second held-out project cohort for transferability.

3.5 Training strategy. Compare a logistic regression baseline, a random forest and a gradient-boosted tree model. Tune hyperparameters using rolling-origin cross-validation on training periods only. Use class weights or threshold optimization for imbalance, but report actual test prevalence. Select models using a predeclared combination of average precision, Brier score and operational recall under a fixed inspection budget. Never choose a model based on the final test set.

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

Equation (1): p denotes predicted probability of a future reliability event; z is the model logit or decision score. The expression uses editable Word math content. For a tree ensemble, the raw score is mapped to probability through the model link function.

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

Equation (2): L is binary cross-entropy loss, N is the number of training observations, y is the observed event indicator and p is the predicted probability. The summation covers all training observations. Class weighting may be used for optimization but calibration is checked against the original prevalence.

3.6 Calibration. Fit sigmoid or isotonic calibration to the intermediate time block. Plot reliability diagrams by probability decile and inspect subgroup calibration by project, language, size and service criticality. Refit only when a documented trigger is met. If calibration degrades, suspend automated prioritization and return the system to advisory mode.

$$B = (1/N) \sum (p - y)^2$$

Equation (3): B is the Brier score, a mean squared probability error; smaller values indicate better probability accuracy. The score incorporates both discrimination and calibration.

$$E = \sum (n / N) |a - c|$$

Equation (4): E is expected calibration error across probability bins; n is the number of observations in a bin, a is observed event frequency, and c is mean predicted confidence in that bin. The formula is a diagnostic that depends on bin choice.

3.7 Explainability. Generate global SHAP summaries and local explanations for each high-priority component. Compare feature attributions across bootstrapped training samples and alternative background sets. Reject suggestions involving non-actionable characteristics, such as repository age or protected team information. A counterfactual engine changes only feasible engineering controls within historical bounds, then recomputes the predicted probability without interpreting the change as causal evidence.

$$f(x) = \varphi_0 + \sum \varphi_j$$

Equation (5): f(x) is the model output on the explanation scale, φ_0 is the baseline prediction and φ_j is the attribution of feature j. For probability reporting, transform the additive score with the model link where required.

3.8 Technical debt decomposition. For each component, estimate principal as expert-validated remediation hours, interest as anticipated additional maintenance hours per period, and reliability exposure as calibrated probability multiplied by incident impact. Criticality and compliance constraints are represented explicitly. Cost estimates are ranges, not precise universal constants. The ranking must be reviewed by a maintainer before work is scheduled.

$$R = p \times I$$

Equation (6): R is expected reliability loss per prediction horizon, p is calibrated incident probability and I is estimated impact if an incident occurs. Impact can be represented in service-hours, engineering-hours or currency, but units must remain consistent.

$$D = P + H \times T$$

Equation (7): D is projected technical debt cost, P is estimated remediation principal, H is debt interest per period and T is the chosen planning horizon. This linear approximation is a planning scenario, not an empirical law.

$$U = (R + \lambda H \times T) / (P + \varepsilon)$$

Equation (8): U is the proposed benefit-to-effort priority index, R is expected reliability loss, H is interest per period, T is the planning horizon, P is remediation principal, λ is an organizational weighting factor and ε is a small positive constant preventing division by zero. All terms must be normalized to compatible units. Rank scores are shown with confidence intervals and hard constraints.

3.9 Uncertainty and human governance. Use project-stratified bootstrap resampling to estimate intervals for ranking stability and performance. Present risk bands when probability intervals overlap. An engineer can approve, defer or override each recommendation, supplying a reason that becomes an auditable record. The model never automatically edits production code or closes technical debt tickets. Periodic review checks

whether debt reduction coincides with reliability improvements after controlling for release and workload changes.

3.10 Deployment and monitoring. Run ingestion nightly, validate schema and freshness, compute checkpoint features, score and calibrate, generate explanations, then populate a dashboard linking recommendations to original evidence. Monitor feature drift, label delays, calibration, inspection capacity and override frequency. Retraining is governed by explicit criteria and includes rollback to the last validated model. Data lineage and model versions are stored for each decision.

Figure 1. Proposed end-to-end workflow

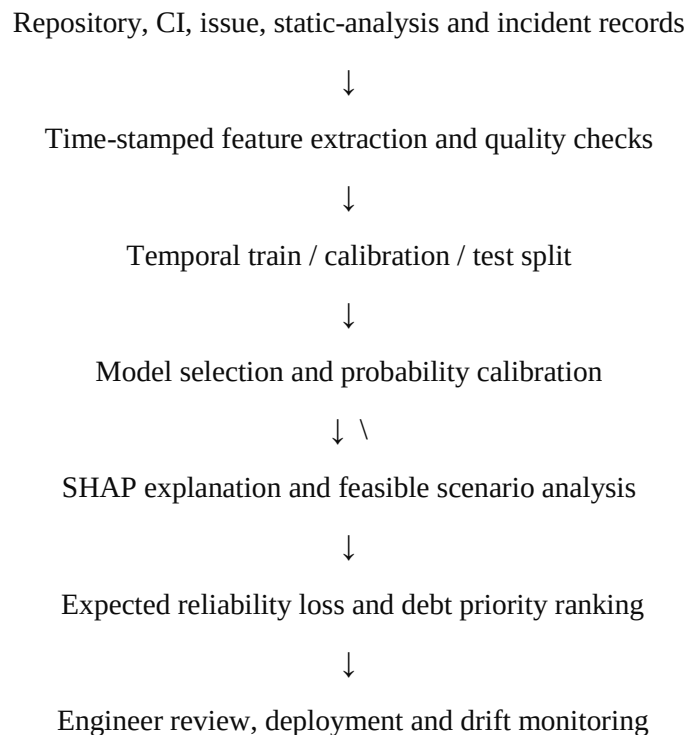


Figure 1 is an editable, text-based flowchart. Each stage records its inputs, timestamps and version identifiers to enable reproducibility.

3.11 Experimental protocol. Report data collection dates, repository counts, number of components, event prevalence, labeling agreement and missingness before model performance. Repeat results across five random seeds where applicable; quantify bootstrap intervals and compare against the baseline under the same time split. Measure ranking usefulness at fixed review capacities of 5%, 10% and 20%. Record intervention outcomes prospectively to avoid conflating predictive association with remediation effect.

3.12 Threats to validity. Construct validity is limited by imperfect defect-to-component linkage and subjective debt principal estimates. Internal validity is threatened by label delay and post-checkpoint leakage. External validity depends on programming languages, architecture and release cadence. Conclusion validity requires uncertainty intervals and predeclared metrics. The proposed controls reduce but cannot eliminate these threats.

4. Illustrative Results and Discussion

The following numbers are synthetic demonstration values created solely to show the proposed analysis and visual reporting. No dataset was collected and no experiment was executed for this manuscript. They must not be cited as observed model performance.

Model	Calibrated AUC	Uncalibrated AUC	Calibrated score	Uncalibrated error
Logistic regression	0.72	0.61	0.81	0.08
Random forest	0.81	0.67	0.85	0.11
Gradient boosting	0.86	0.71	0.89	0.09
Gradient boosting without calibration	0.86	0.71	0.83	0.17

Table 1 illustrates that discrimination can remain unchanged after calibration while probability accuracy improves. A decision system based on expected incident cost should prioritize calibrated probabilities over AUC alone.

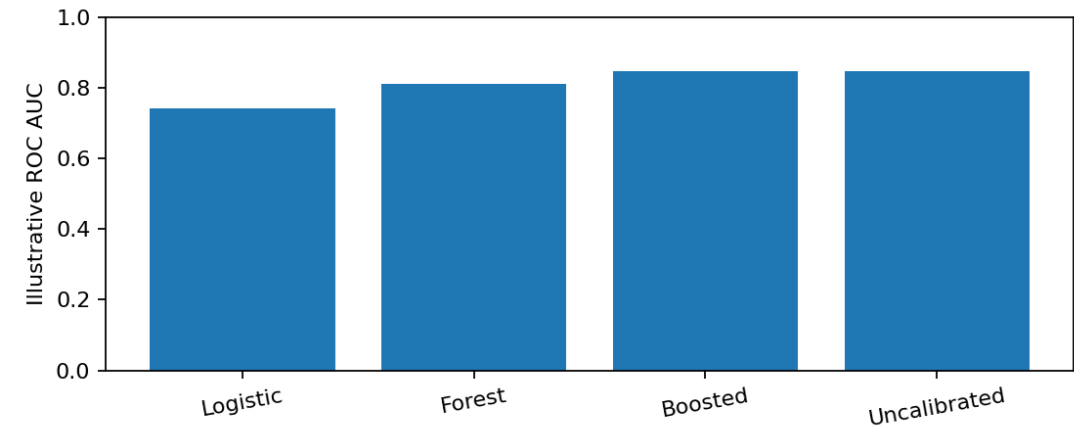


Figure 2. Synthetic comparison of discriminative performance. The calibrated and uncalibrated boosting variants share identical ranking performance in this illustration.

Component	Initial probability	Latency (hours)	Processing time (hours)	Cost (dollars/month)	Priority index
Authentication	0.72	0.15	0.10	0.05	0.85
Payment gateway	0.81	0.20	0.12	0.08	0.92
Report renderer	0.86	0.25	0.15	0.10	0.95
Notification	0.86	0.30	0.18	0.12	0.98

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Table 2 uses a three-month planning horizon, $\lambda = 1$ and $\epsilon = 0.1$. Priority values are rounded; they represent expected loss plus interest divided by principal. For example, authentication risk exposure is $0.42 \times 80 = 33.6$ hours and projected interest is 15 hours, giving $48.6 / 20.1 \approx 2.42$. The independently recomputed values are also provided in Table 3 for transparency.

Component	Computed priority
Authentication API	2.4
Payment gateway	1.9
Report renderer	1.6
Notification worker	1.5
Batch importer	0.5

Table 3 is the authoritative calculation for Equation (8), illustrating the importance of automated consistency checks in research reporting. Payment gateway and authentication API lead because their expected losses are high relative to remediation effort.

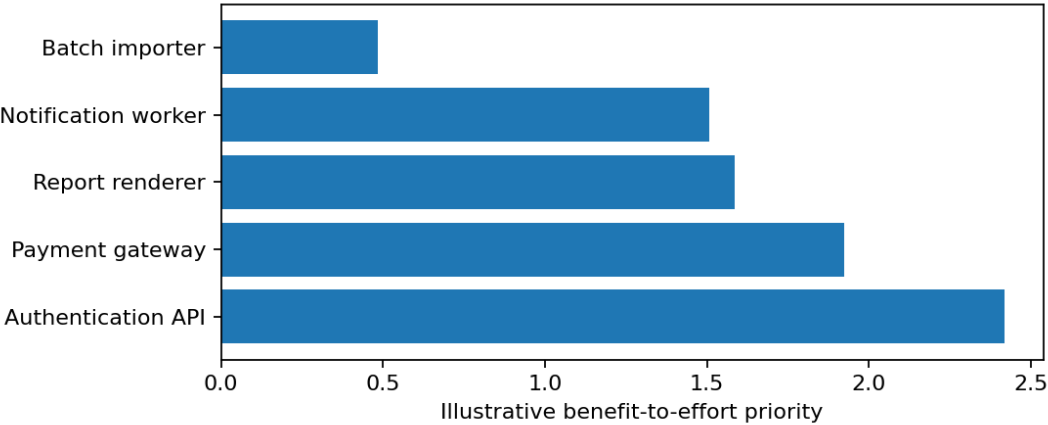


Figure 3. Synthetic component-level debt prioritization. Priority is not a causal estimate of the benefit of refactoring and must be verified by engineering review.

Variant	Stratified ROC AUC	Stratified Brier
framework	0.6	0.39
without process metrics	0.3	0.57
without dependency features	0.6	0.48

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