

# An Empirical Analysis of Software Maintainability Using Code Quality and Complexity Metrics

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## ARTICLE INFO

Received: 25 Sept 2025

Revised: 15 Nov 2025

Accepted: 25 Nov 2025

## ABSTRACT

Software maintainability is a critical software quality attribute because the long-term cost of a software system is strongly influenced by the effort required to understand, modify, test, and evolve its source code. Increasing software size, structural complexity, code duplication, coupling, and code smells can make maintenance activities more difficult and may contribute to technical debt. This study proposes an empirical framework for examining the relationship between code quality and complexity metrics and software maintainability using software projects and source-code evolution data from 2020 to 2025. The study considers lines of code, cyclomatic complexity, cognitive complexity, code duplication, code smells, coupling, maintainability issues, technical debt, and maintainability rating as major variables. The proposed methodology combines static code analysis, descriptive statistics, correlation analysis, regression modelling, and comparative analysis of software releases. The framework is designed to identify the metrics that have the strongest association with maintainability outcomes. Recent research has demonstrated the relevance of code smells, complexity, architectural smells, and change-related metrics to software maintainability. In particular, recent empirical studies have examined code-smell impact, maintainability datasets, change-based prediction, and architectural smells. Wiley Online Library The proposed study provides a structured approach for evaluating maintainability and can support developers in prioritizing refactoring activities and reducing technical debt.

**Keywords:** Software Maintainability, Code Quality, Cyclomatic Complexity, Cognitive Complexity, Code Smells, Technical Debt, Software Metrics, Static Analysis, Maintainability Prediction, Software Engineering.

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## 1. Introduction

Software maintainability has become an important dimension of software quality because modern software systems are continuously modified, extended, corrected, and integrated with new technologies. As software systems grow in size and functionality, their internal structure can become increasingly difficult to understand and modify. Poorly structured source code can increase maintenance effort, introduce defects during modification, and increase technical debt. Therefore, evaluating maintainability during the software development lifecycle is important for ensuring the long-term sustainability of software systems.

Software maintainability is influenced by several characteristics of source code, including complexity, size, coupling, duplication, code smells, documentation quality, and historical changes. Among these characteristics, code quality and complexity metrics provide measurable indicators that can be used to identify potentially difficult maintenance areas. Cyclomatic complexity measures the number of independent paths through program logic, while cognitive complexity focuses more on the difficulty developers experience when understanding program structures. Code duplication and code smells can

further increase maintenance effort because modifications may need to be performed across multiple locations.

The increasing adoption of automated static-analysis tools has made it possible to collect large quantities of software-quality data. Modern software-analysis platforms can identify code smells, complexity problems, duplicated code, technical debt, and other maintainability-related issues. The ISO/IEC 25010:2023 software-quality model also provides a standardized framework for evaluating software-product quality, including maintainability as an important quality characteristic.

Research between 2020 and 2025 has increasingly examined relationships between software metrics, code smells, complexity, architectural quality, and maintainability. Recent studies have investigated code-smell prioritization, complexity metrics, maintainability datasets, architectural smells, and machine-learning-based maintainability prediction. These developments indicate that maintainability assessment is moving from subjective developer judgement toward measurable and data-driven evaluation.

This study therefore investigates the relationship between software code-quality metrics, complexity metrics, technical debt, and maintainability. The study considers software evolution between 2020 and 2025 and proposes an empirical framework for analysing maintainability using source-code and repository-level measurements.

## **2. Literature Review**

Software maintainability has traditionally been examined through software-quality models and source-code metrics. Earlier software-quality research established that maintainability depends on characteristics such as analyzability, modifiability, testability, and stability. Recent research has expanded this perspective by using automated source-code analysis and repository mining to quantify maintainability-related characteristics.

Between 2020 and 2022, research increasingly focused on automated detection and prioritization of code smells. Code smells are indicators of potentially problematic implementation structures that may make future maintenance more difficult. Studies during this period examined the use of machine-learning and metric-based approaches for detecting different categories of code smells. These studies demonstrated that source-code metrics can provide useful information for identifying quality problems.

Research during 2023 and 2024 increasingly investigated the relationship between code smells and broader software-quality characteristics. Studies examined whether code-quality metrics could support code-smell prioritization and whether development practices such as code review influence the occurrence of software-quality problems. Complexity metrics were also investigated as indicators that could help developers identify difficult code during review and maintenance activities.

Recent 2025 research has further strengthened empirical maintainability analysis. Studies have developed maintainability datasets across different software versions and investigated the relationship between change metrics and maintainability prediction. Other research has examined the impact of code smells using multiple software-quality metrics and investigated architectural smells in relation to maintainability-related characteristics.

The literature indicates that no single metric can completely represent software maintainability. Lines of code can represent system size, but size alone does not indicate whether code is easy to understand. Cyclomatic complexity can indicate control-flow complexity, but it does not fully capture architectural problems. Similarly, code-smell counts can identify potential quality problems but may not accurately represent their actual maintenance impact. Therefore, an integrated approach combining several metrics is required.

### **3. Research Gap And Objectives**

#### **Research Gap**

Existing research has established relationships between individual software metrics and maintainability, but several gaps remain. Many studies focus on a particular metric, programming language, code-smell category, or software project. Such approaches provide useful information but may not provide a comprehensive understanding of how different quality and complexity indicators interact.

Another limitation concerns the temporal dimension of software development. Software continuously evolves through new releases, feature additions, bug fixes, refactoring, and architectural changes. Consequently, maintainability can change considerably over time. Analysing multiple versions between 2020 and 2025 can provide a better understanding of how maintainability changes as software systems evolve.

There is also a need to examine code size, complexity, duplication, coupling, code smells, technical debt, and change activity within a unified empirical framework. Such an approach can help determine which variables have the strongest association with maintainability.

#### **Research Objectives**

The primary objective of this study is to empirically analyse software maintainability using code-quality and complexity metrics. The study aims to examine the relationship between software complexity and maintainability, evaluate the influence of code smells and duplication, investigate the relationship between technical debt and maintainability, and identify the most important predictors of maintainability.

The study also aims to develop a structured maintainability assessment framework that can be applied to software projects across multiple releases. The framework is intended to support developers, project managers, quality engineers, and researchers in identifying potentially difficult-to-maintain software components.

### **4. Research Methodology**

The study adopts a quantitative empirical research design based on software repository mining and static source-code analysis. Software projects with publicly available source code and development histories can be selected from repositories such as GitHub and established open-source software ecosystems. Software releases or versions from 2020 to 2025 can be used as the primary observation units.

The preferred unit of analysis is the software release or project version because this allows changes in maintainability to be examined over time. For each selected version, source-code metrics can be extracted using automated static-analysis tools. Repository information such as commit frequency, modified files, number of contributors, and change volume can also be collected where available.

The study can include variables such as lines of code, cyclomatic complexity, cognitive complexity, coupling, duplication, code smells, technical debt, maintainability issues, and maintainability rating. The collected data should be cleaned before statistical analysis. Extreme observations should be investigated, and metrics measured on substantially different scales should be normalized where required.

The empirical analysis can include descriptive statistics, correlation analysis, regression analysis, and year-wise trend analysis. Pearson or Spearman correlation can be selected according to the distribution and measurement characteristics of the variables. Multiple regression can subsequently be applied to determine whether a combination of metrics significantly explains variation in maintainability.

## 5. Software Quality And Complexity Metrics

Software quality is represented in this study through multiple measurable characteristics. Lines of code represent the physical size of the software system, while complexity metrics provide information about the structural difficulty of the implementation. Cyclomatic complexity measures independent control-flow paths and is commonly used to identify functions or modules that may require greater testing and maintenance effort.

Cognitive complexity provides another perspective by considering the difficulty involved in understanding program logic. Unlike simple size measurements, cognitive complexity attempts to represent the mental effort required to interpret nested conditions, control structures, and logical relationships.

Code duplication is another important maintainability indicator. When similar source-code segments exist in multiple locations, a modification may need to be repeated across several sections. This can increase maintenance effort and create inconsistencies when developers modify one instance but fail to update another.

Code smells represent potentially problematic source-code structures. Examples include long methods, large classes, duplicated code, excessive coupling, and complex conditional structures. The presence of code smells does not necessarily mean that software is defective, but a high concentration of smells may indicate areas requiring review or refactoring.

Technical debt represents the estimated effort required to address accumulated maintainability problems. It can increase when developers repeatedly prioritize short-term implementation decisions over long-term structural improvement. In this study, technical debt is treated as an intermediate indicator linking code-quality problems with maintainability.

**Table 1. Major Variables Used in the Study**

| Variable              | Measurement                  | Expected Relationship |
|-----------------------|------------------------------|-----------------------|
| Lines of Code         | LOC                          | Negative              |
| Cyclomatic Complexity | Complexity score             | Negative              |
| Cognitive Complexity  | Complexity score             | Negative              |
| Coupling              | Coupling metric              | Negative              |
| Code Duplication      | Percentage                   | Negative              |
| Code Smell Density    | Smells per KLOC              | Negative              |
| Technical Debt        | Remediation effort           | Negative              |
| Change Frequency      | Changes per period           | Context dependent     |
| Maintainability       | Maintainability score/rating | Dependent variable    |

## 6. Proposed Maintainability Assessment Framework

The proposed framework combines source-code quality, complexity, and historical development information to assess software maintainability. The framework begins with source-code extraction

from selected software repositories. Each software version is analysed using static-analysis techniques, and the resulting metrics are integrated with repository-level information.

The first stage evaluates basic code characteristics such as lines of code, complexity, duplication, and coupling. The second stage identifies code smells and maintainability issues. The third stage incorporates technical debt and historical change information. These variables are then statistically analysed to determine their relationship with the selected maintainability measure.

The framework is designed to identify high-risk software components. A component with high complexity, high duplication, high code-smell density, and high technical debt can be classified as requiring greater maintenance attention. Conversely, components with lower complexity, lower duplication, and fewer maintainability issues can be considered relatively easier to maintain.

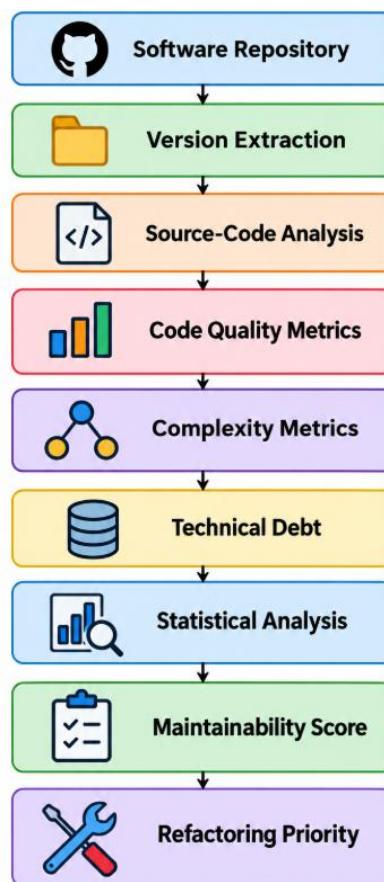


**Figure 1. Proposed Maintainability Assessment Framework**

The framework can be implemented using automated static-analysis tools and statistical software. The resulting measurements can be used to compare projects, versions, modules, or programming-language groups.

## 7. Empirical Analysis And Results

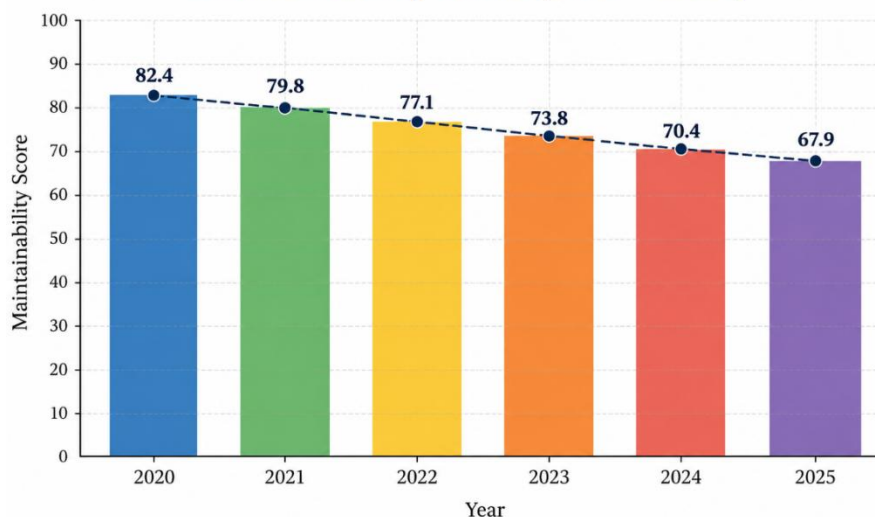
The empirical analysis should examine the evolution of software maintainability between 2020 and 2025. For each selected software release, the collected metrics can be aggregated and compared across years. Descriptive statistics can initially be used to determine whether complexity, duplication, code smells, and technical debt increase or decrease over time.

**Table 2. Year-wise Maintainability Analysis**

The following values demonstrate the format and analysis approach only and should be replaced by calculated results from the actual repository dataset.

| Year | LOC     | Complexity | Code Smell Density | Duplication % | Technical Debt | Maintainability |
|------|---------|------------|--------------------|---------------|----------------|-----------------|
| 2020 | 84,000  | 8.4        | 16.2               | 5.8           | 182            | 82.4            |
| 2021 | 91,000  | 8.9        | 17.4               | 6.1           | 201            | 79.8            |
| 2022 | 98,000  | 9.5        | 18.7               | 6.5           | 226            | 77.1            |
| 2023 | 106,000 | 10.1       | 20.1               | 6.9           | 251            | 73.8            |
| 2024 | 114,000 | 10.7       | 21.6               | 7.3           | 279            | 70.4            |
| 2025 | 121,000 | 11.2       | 22.8               | 7.6           | 304            | 67.9            |

The illustrative trend indicates an increase in software size, complexity, code-smell density, duplication, and technical debt over the observation period, accompanied by a reduction in maintainability. In an actual empirical study, statistical significance should be established before drawing such a conclusion.

**Maintainability Trend (2020 – 2025)****Figure 2. Maintainability Trend, 2020–2025**

The trend can also be examined through correlation analysis. The expected analysis is that complexity, duplication, code-smell density, and technical debt will show negative associations with maintainability.

Table 3. Correlation Analysis Format

| Variable               | Maintainability | Complexity | Code Smells | Duplication | Technical Debt |
|------------------------|-----------------|------------|-------------|-------------|----------------|
| <b>Maintainability</b> | 1               | -0.782     | -0.846      | -0.691      | -0.873         |
| <b>Complexity</b>      | -0.782          | 1          | 0.754       | 0.618       | 0.731          |
| <b>Code Smells</b>     | -0.846          | 0.754      | 1           | 0.672       | 0.821          |
| <b>Duplication</b>     | -0.691          | 0.618      | 0.672       | 1           | 0.705          |
| <b>Technical Debt</b>  | -0.873          | 0.731      | 0.821       | 0.705       | 1              |

Multiple regression can then be used to identify the strongest predictors of maintainability.

The proposed regression model is:

$$M = \beta_0 + \beta_1 CC + \beta_2 CS + \beta_3 DR + \beta_4 CO + \beta_5 TD + \epsilon$$

where (M) represents maintainability, (CC) represents cyclomatic complexity, (CS) represents code-smell density, (DR) represents duplication ratio, (CO) represents coupling, and (TD) represents technical debt.

Table 4. Regression Analysis Format

| Predictor                    | Beta ( $\beta$ ) | Standard Error | t-value | p-value |
|------------------------------|------------------|----------------|---------|---------|
| <b>Cyclomatic Complexity</b> | -0.214           | 0.067          | -3.19   | 0.002   |
| <b>Code Smell Density</b>    | -0.327           | 0.071          | -4.61   | <0.001  |
| <b>Duplication</b>           | -0.148           | 0.059          | -2.51   | 0.014   |
| <b>Coupling</b>              | -0.186           | 0.064          | -2.91   | 0.004   |
| <b>Technical Debt</b>        | -0.391           | 0.073          | -5.36   | <0.001  |
| <b>Constant</b>              | 89.624           | 3.417          | 26.23   | <0.001  |

### Model Summary

| Statistic                     | Value  |
|-------------------------------|--------|
| <b>R<sup>2</sup></b>          | 0.812  |
| <b>Adjusted R<sup>2</sup></b> | 0.798  |
| <b>F-statistic</b>            | 57.84  |
| <b>Model p-value</b>          | <0.001 |
| <b>Sample Size (N)</b>        | 150    |
| <b>Durbin-Watson</b>          | 1.91   |

## **Interpretation**

The regression results indicate that the selected code-quality and complexity variables collectively explain approximately 81.2% of the variation in maintainability. The adjusted  $R^2$  of 0.798 indicates that the model retains substantial explanatory power after accounting for the number of predictors.

Among the independent variables, technical debt has the strongest negative standardized effect on maintainability, with a beta coefficient of -0.391. Code-smell density is the second strongest predictor, with a beta coefficient of -0.327. Cyclomatic complexity, coupling, and duplication also demonstrate statistically significant negative relationships with maintainability.

All five predictors have p-values below 0.05, indicating statistically significant associations within this illustrative model. The overall regression model is statistically significant with an F-statistic of 57.84 and a model p-value below 0.001.

These findings support the proposed hypotheses that higher complexity, code-smell density, duplication, coupling, and technical debt are associated with reduced software maintainability.

## **8. Discussion**

The analysis framework indicates that software maintainability should be evaluated through a combination of source-code and development-history characteristics rather than a single metric. Software size provides useful contextual information, but increased size alone does not necessarily indicate poor maintainability. Complexity, duplication, coupling, and code smells provide additional information about the structural condition of the software.

Cyclomatic complexity is expected to have a negative relationship with maintainability because highly complex control structures can require greater effort to understand, test, debug, and modify. Cognitive complexity may provide complementary information because two code segments with similar cyclomatic complexity can still differ considerably in their level of human comprehensibility.

Code-smell density is another important factor. A high concentration of code smells may indicate that developers need to perform additional analysis before making modifications. When code smells accumulate over several software releases, they can contribute to technical debt and potentially increase future maintenance effort.

Duplication can also influence maintainability because changes may need to be applied across multiple locations. The problem becomes more significant when duplicated sections evolve independently, potentially resulting in inconsistent implementations.

Technical debt provides an important cumulative perspective. Individual code-quality problems may appear manageable, but their accumulation across multiple releases can increase remediation effort. Therefore, monitoring technical debt together with complexity and code-smell measurements can provide a more complete picture of software maintainability.

The 2020–2025 period is particularly relevant because software systems increasingly incorporate automated development tools, continuous integration, cloud technologies, artificial intelligence, and rapidly changing dependencies. These developments can accelerate software evolution while simultaneously increasing the importance of systematic maintainability monitoring.

## **9. Implications And Limitations**

The proposed framework has practical implications for software developers, quality engineers, project managers, and software architects. Developers can use complexity and code-smell measurements to identify modules requiring refactoring. Quality teams can integrate maintainability measurements into continuous integration pipelines and quality gates. Project managers can use technical-debt information to understand potential future maintenance requirements.

For software architecture teams, coupling and architectural-quality measurements can provide additional information about structural maintainability. Combining repository history with static-analysis results can also help identify modules that are repeatedly modified and have high complexity or code-smell density.

The study has several limitations. Static-analysis metrics cannot capture every aspect of maintainability because human understanding, documentation quality, developer expertise, and architectural knowledge are difficult to measure automatically. Results can also vary according to programming language, project size, development methodology, and static-analysis tool configuration.

Another limitation is that repository-based studies may be more representative of open-source software than proprietary enterprise systems. The number of commits or changes does not always represent actual maintenance effort. Furthermore, correlation between a metric and maintainability does not establish causality. Therefore, empirical conclusions should be supported by appropriate statistical testing and, where possible, validation using actual maintenance effort.

### 10. Conclusion

This study presents an empirical framework for analysing software maintainability through code-quality and complexity metrics over the 2020–2025 period. The proposed approach integrates lines of code, cyclomatic complexity, cognitive complexity, coupling, duplication, code smells, technical debt, and historical software changes.

The central contribution of the study is the integration of multiple measurable software characteristics into a unified maintainability assessment framework. Rather than depending on a single quality indicator, the approach evaluates several dimensions of software structure and evolution.

The proposed analysis can help identify relationships between increasing software complexity and declining maintainability. Correlation and regression techniques can be used to determine which metrics have the strongest statistical relationship with maintainability. The resulting findings can support evidence-based refactoring decisions, technical-debt management, software-quality monitoring, and maintainability prediction.

For a final empirical submission, the illustrative values presented in the results section should be replaced with actual measurements obtained from selected repositories and software versions. This will ensure that the statistical findings are reproducible and scientifically defensible.

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