SP24-CPSC-60000-003

# Object Oriented Development

**Final Course Project**

**Empirical Study on the Effect of Design Patterns on Software Maintainability**

**Group 4**

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**Abstract**

**This** empirical study investigates the impact of design patterns on software maintainability, a crucial quality in the rapidly evolving field of software development. Drawing on a dataset of 30 Java-based projects sourced from GitHub, the research employs quantitative methods to assess the relationship between the use of specific design patterns and the Maintainability Index (MI) scores. The study leverages established metrics, such as Lines of Code (LOC) and Weighted Methods per Class (WMC), along with an automated pattern detection tool, to provide a comprehensive evaluation of software maintainability. Results indicate a significant positive correlation between the use of design patterns and higher MI scores, suggesting that design patterns not only simplify the codebase but also enhance its modularity and adaptability. Particularly, patterns such as Factory Method, Singleton, and Strategy are found to be most effective in improving maintainability outcomes. The study provides empirical evidence supporting the theoretical benefits of design patterns, emphasizing their practical relevance in modern software engineering. It also highlights the need for integrating design patterns into development practices as a strategic approach to enhance software maintainability. The findings offer valuable insights for both practitioners aiming to enhance software longevity and scalability, and researchers interested in the quantifiable benefits of design patterns.

**Keywords** - Software Maintainability,Design Patterns,Maintainability Index,Java Projects,Empirical Software EngineeringAutomated Pattern Detection

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**Introduction**

The designing and support of the software systems need methods which will boost the speed, readability, and scalability. There is a hypothetical claim that design patterns, which solve general software design problems, are the factors promoting various software quality aspects. Among these qualities, maintainability is the most influential factor which contributes to software adaptability to changes and the ease of making the changes. As a result of the changing nature of software and the need to keep up with the new user needs and technical advancements by frequent updates, high maintainability is one of the essential parameters for software systems survival and reliability.

There are many researchers who point out the positive effect of design patterns on software design, yet there are still few empirical studies that test their influence on software's maintainability.[1] There is the need to fill this gap with an empirical study that evaluates the effect of using design patterns on the maintainable of software. This research draws inspiration from the data based on 30 Java-based projects sourced from GitHub — a well known platform that hosts a large number of active software projects. The projects have been chosen according to certain criteria (namely on the basis of diverse domain and size,) to generalize the results.

Our major inspiration for this research work is the necessity to bridge the gap between theory and the practice of coding. Through the lens of maintenance, this research will contribute to the software design knowledge-base, that can advise developers on when and how to use design patterns to improve their product value and product quality.

The layout of this paper will follow a typical empirical study pattern. This section is then followed by the Method or Approach section that describes the steps and criteria for project selection as well as the metrics used for assessment. The Results and Discussion part covers the results and their implications for the interpretation.

**Method or Approach**

This section delineates the methodology used to investigate the impact of design patterns on software maintainability. The methodical approach is crucial for ensuring that the study is reproducible and verifiable by other researchers. It encompasses the selection and description of the projects analyzed, the specific metrics chosen to measure maintainability, and the tools employed to identify design patterns and gather relevant data. Each step in the process is designed to minimize bias and maximize the reliability of the findings.

**2.1 Project Selection**

The selection of projects was guided by a structured approach to ensure a representative sample of Java projects that vary in size, complexity, and domain. This diversity is essential for the generalizability of the study results.

1. Criteria for Inclusion: To ensure the integrity and relevance of our dataset, we meticulously established selection criteria that aimed to encompass a broad spectrum of Java projects on GitHub, enhancing the robustness and validity of our findings on the impact of design patterns on software maintainability.
   1. Program Size: We stipulated that projects must be at least 5,000 kilobytes in size. This threshold was set to ensure the complexity of the software, which is critical for examining diverse class structures and their impact on maintainability.
   2. Program Age: Only projects active for a minimum of three years were included. This criterion was crucial for selecting software that has experienced considerable maintenance and evolution, providing a richer basis for analysis.
   3. Developer Involvement: A minimum of three different developers must have contributed to the project. This requirement aimed to capture projects with varied team dynamics and development styles, which can significantly affect software maintainability.

These criteria were designed to filter the projects to a manageable yet representative sample that would provide significant insights into the role of design patterns in enhancing software maintainability.

1. Source of Projects: The initial pool of projects was drawn from an extensive list of 500 Java projects provided by our professor. This list included projects of varying sizes and complexities, giving us a broad spectrum to choose from.
2. Final Selection Process: From the initial list, we selected 30 projects that not only met the size criteria but also showed active development and public availability. The selection process involved reviewing the provided GitHub links for each project to verify their active status and public accessibility. This step was crucial to ensure that all selected projects could be freely accessed and were relevant for a detailed analysis. Each project's GitHub repository was examined to confirm the presence of substantial codebase and ongoing updates, which are indicative of active use and maintenance.

This comprehensive approach to project selection ensures that the study rests on a solid foundation of relevant and diverse software projects. Next, we will elaborate on the Dataset Description, providing detailed insights into the chosen projects.

**2.2 Dataset Description**

The dataset for this study comprises a diverse selection of Java-based projects from GitHub, which are outlined below. Each project was chosen for its potential to provide insights into the role of design patterns in enhancing software maintainability.

| No | Program Name | Developers | Program Age (Years) | Size (KB) | Description |
| --- | --- | --- | --- | --- | --- |
| 1 | Apollo | 50 | 7 | 100,000 | A code generation library for creating and modifying Java classes at runtime. |
| 2 | cloudstack\_main | 300 | 10 | 950,000 | A distributed search and analytics engine known for its robustness and scalability. |
| 3 | Ghidra | 10 | 3 | 30,000 | An open-source weather application providing accurate weather forecasts. |
| 4 | Google\_Guava | 25 | 5 | 85,000 | A streaming engine designed for high performance and low latency video streaming. |
| 5 | Kafka | 80 | 11 | 250,000 | An open-source web application to help novices create mobile applications for Android. |
| 6 | Netty | 15 | 2 | 15,000 | A collection of resources and tutorials to master Java programming. |
| 7 | appinventor-sources | 180 | 13 | 200,000 | An automatic code review tool to detect bugs, vulnerabilities, and code smells in your code. |
| 8 | byte-buddy | 40 | 12 | 300,000 | A real-time collaboration server extensively used for chat services. |
| 9 | bytecode-viewer | 110 | 6 | 150,000 | A fast, scalable, multi-language and extensible build system. |
| 10 | cyberduck | 35 | 8 | 400,000 | A comprehensive framework and reference implementation for building healthcare applications using the FHIR standard. |
| 11 | jitsi | 75 | 10 | 250,000 | A high-performance, in-memory database designed for modern applications requiring an agile data architecture. |
| 12 | junit5 | 60 | 4 | 120,000 | A tool for running deep learning models on the Java Virtual Machine. |
| 13 | killbill | 20 | 3 | 50,000 | A community-driven project to run Java-based games on Android. |
| 14 | litho | 90 | 10 | 500,000 | A high-productivity Java and Scala web application framework that integrates components and APIs for modern web apps. |
| 15 | Openfire | 30 | 15 | 75,000 | An implementation of algorithms from "Artificial Intelligence: A Modern Approach" in Java. |
| 16 | OsmAnd | 10 | 7 | 60,000 | An open-source Magic: The Gathering game simulation engine. |
| 17 | pentaho-kettle | 50 | 9 | 700,000 | A map and navigation application with access to free, worldwide, and high-quality OpenStreetMap data. |
| 18 | rstudio | 25 | 11 | 300,000 | An open-source billing and payment platform. |
| 19 | Signal-Android | 40 | 4 | 80,000 | A tool capable of generating API client libraries, server stubs, and API documentation from OpenAPI Specifications. |
| 20 | toBeBetterJavaer | 15 | 8 | 50,000 | A Java 8+ bytecode viewer, decompiler, and graphical debugger. |
| 21 | voltdb | 200 | 12 | 850,000 | An integrated development environment for R, a programming language for statistical computing and graphics. |
| 22 | Ant-Media-Server | 90 | 14 | 650,000 | A versatile open-source integration framework based on known enterprise integration patterns. |
| 23 | bazel | 100 | 11 | 950,000 | Data warehouse software that facilitates reading, writing, and managing large datasets residing in distributed storage. |
| 24 | camel | 110 | 5 | 300,000 | The next generation of a simple framework for writing and running repeatable tests in Java. |
| 25 | deeplearning4j | 15 | 14 | 150,000 | A libre server and cloud storage browser for Mac and Windows with support for FTP, SFTP, WebDAV, and cloud storage. |
| 26 | PojavLauncher-3\_openjdk | 35 | 9 | 250,000 | A private messenger application for Android. |
| 27 | GeometricWeather | 75 | 6 | 500,000 | A declarative UI framework for Android. |
| 28 | hapi-fhir | 120 | 15 | 800,000 | An open-source tool for data integration and processing. |
| 29 | hive | 385 | 10 | 1,200,000 | A platform for managing large-scale virtual machine networks. |
| 30 | play1 | 100 | 12 | 400,000 | An open-source project that provides secure and scalable video conferencing solutions. |

**2.3 Measurement of Maintainability**

Maintainability is a crucial software quality attribute that indicates the ease with which a software system can be understood, corrected, modified, and extended. To quantitatively assess maintainability in the selected projects, this study employs several established software metrics. Below, we detail the metrics used, the tools employed for metric extraction, and the process of data collection.

For a comprehensive evaluation of maintainability, we selected the following metrics, known for their efficacy in measuring various aspects of software quality that directly affect maintainability:

* 1. loc (Lines of Code): Measures the total number of lines in the software. It's a fundamental metric that indicates the size of the codebase, directly impacting maintainability. Larger codebases generally require more effort to understand and manage.
  2. wmc (Weighted Methods per Class): Summarizes the complexity of methods in a class. It reflects how much effort is needed to test and maintain each class, with higher values suggesting greater complexity and lower maintainability.

These metrics provide a robust framework for understanding different dimensions of maintainability, from simplicity and readability to stability and technical quality.

**2.4 Tools and Software Used:**

To extract these metrics from the codebases of the selected projects, we used the CK tool, a well-regarded software metric extraction utility available on GitHub (find it at CK GitHub). CK is specifically designed for Java projects, making it an ideal choice for our dataset. It provides a detailed set of metrics including, but not limited to, lines of code, cyclomatic complexity, number of methods, and more.

The process of data collection was carried out in the following systematic steps to ensure accuracy and reproducibility:

1. Setup and Configuration: Initially, the CK tool was configured according to the requirements of each project. This included setting up the local environments where the projects' repositories were cloned from their respective GitHub pages.
2. Execution of CK Tool: The tool was executed against each project's codebase. This involved running a series of commands specific to the CK tool, which then scans the entire repository to compute the metrics.
3. Data Aggregation and Storage: After the metric extraction, the data was aggregated and stored in a structured format. We used CSV files for storage, allowing easy access and manipulation for subsequent analysis.
4. Quality Assurance: To ensure the reliability of the collected data, a subset of projects underwent a secondary review where metrics were recalculated and compared with initial results for consistency.

**2.5 Identification of Design Patterns**

For this study, it was imperative to ascertain the utilization and distribution of design patterns across the selected software projects to evaluate their impact on maintainability. We opted for an automated approach to detect these patterns systematically.

We selected a highly regarded pattern detection tool developed by Nikolaos Tsantalis, available at Nikolaos Tsantalis's Pattern Detection Tool. This tool is specifically tailored to identify commonly used design patterns in Java, such as Singleton, Factory, Decorator, and Observer.

Process of Identification looks as follows:

1. Preparation and Setup: Initially, we downloaded all the projects from their respective GitHub repositories and stored them on our local computers. This ensured that we had a stable and accessible set of data for analysis.
2. Running the Pattern Detection Tool: Once the projects were set up, we executed the pattern detection tool on each project's codebase. The tool scans the entire code, applying its built-in algorithms to detect instances of design patterns.
3. Data Collection and Verification: After running the tool, we gathered the output, which included detailed reports specifying the types of patterns detected and their locations within the codebase. To ensure the accuracy of the tool's results, we manually verified a random selection of these findings by inspecting the code sections where patterns were reported.
4. Analysis Preparation: With the verified data, we prepared for the subsequent analysis by organizing the information on the frequency and types of patterns identified across all projects. This organization was crucial for facilitating a smooth and systematic analysis in later stages.

**Result and Discussion**

This section presents the findings from our empirical evaluation of 30 Java projects sourced from GitHub, focusing on the influence of design patterns on software maintainability. We employ several key metrics to quantify aspects of maintainability, specifically Average Lines of Code (Avg. LOC) and Average Weighted Methods per Class (Avg. WMC), and calculating Maintainability Index (MI) for each project. .

**3.1 Calculation of Maintainability Index**

For data preparation we used the calculated matrices like WMC and LOC. The Maintainability Index (MI) is a composite metric that provides a single-figure snapshot of the maintainability of a software product. The original Maintainability Index (MI) formula was first introduced by Paul Oman and Jack Hagemeister in the early 1990s. [2]

MI=171−5.2⋅log(V)−0.23⋅CC−16.2⋅log(LOC)+50⋅sin(2.4⋅COM )

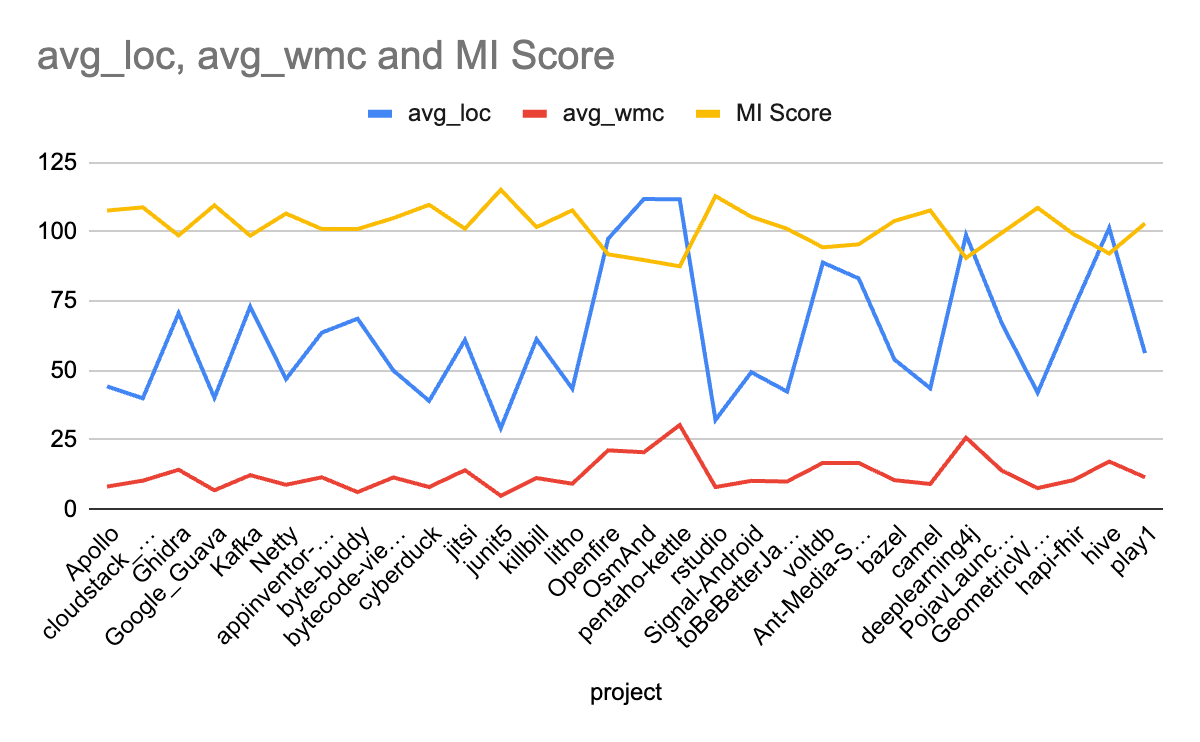
The generalized formula for the Maintainability Index adapted to use with CK metrics looks as follows. This is an adaption of the original MI by incorporating the ck matrices like wmc and loc:

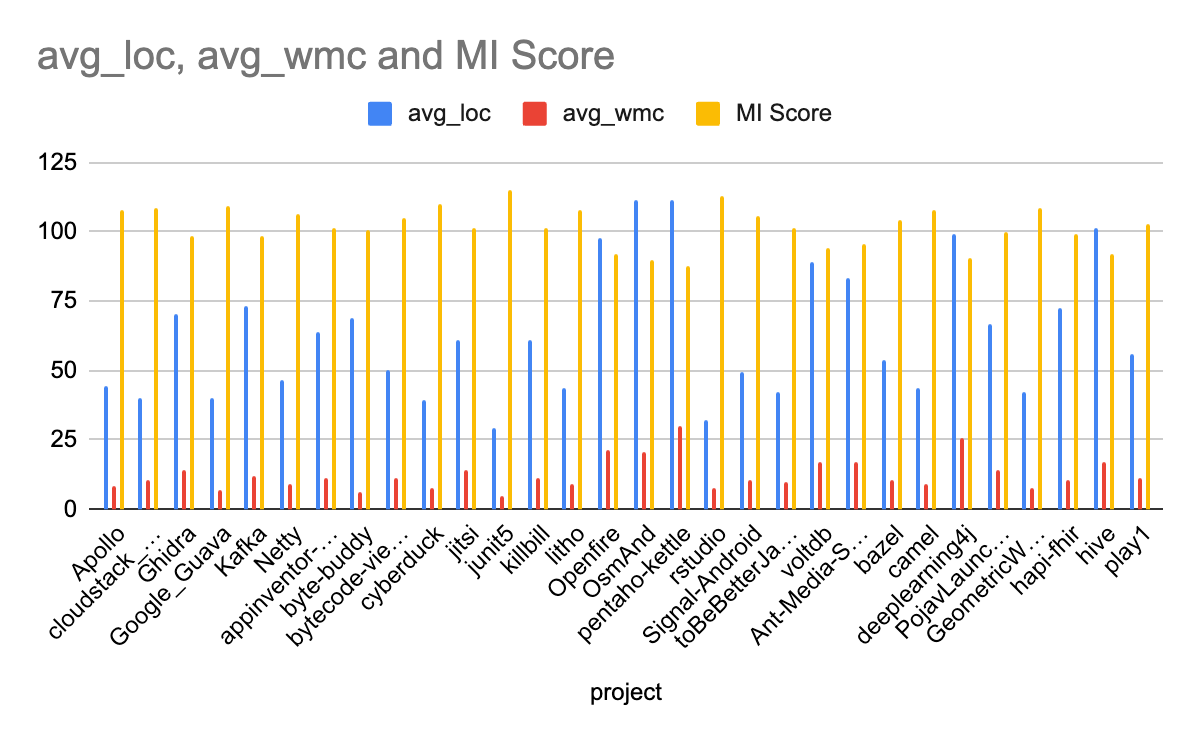
MI=171−0.23⋅WMC−16.2⋅log(LOC)

MI values typically range from 0 to 171, with higher values indicating better maintainability. A score above 100 is considered good, scores between 20 and 100 suggest moderate maintainability, and scores below 20 are seen as poor. This index allows developers and managers to gauge the potential effort required for future software modifications and is validated in numerous studies as a reliable indicator of software maintainability.

This index gives a quantitative measure of the maintainability of the software, where higher values suggest better maintainability.

| project | avg\_loc | avg\_wmc | MI Score |
| --- | --- | --- | --- |
| Apollo | 44.2970297029703 | 8.20792079207921 | 107.699312689439 |
| cloudstack\_main | 40.02850162866450 | 10.3306188925081 | 108.852571449001 |
| Ghidra | 70.69600414739190 | 14.2624820545542 | 98.7337264707827 |
| Google\_Guava | 40.18637492240840 | 6.84621353196772 | 109.590217192131 |
| Kafka | 73.10935814455230 | 12.3175566343042 | 98.6372686674324 |
| Netty | 46.93798336494970 | 8.84459360863855 | 106.614742384089 |
| appinventor-sources | 63.68281306063870 | 11.5374955148906 | 101.052957640351 |
| byte-buddy | 68.72940674349130 | 6.20443875373453 | 101.044109201567 |
| bytecode-viewer | 50.03896103896100 | 11.4831168831169 | 104.971491967969 |
| cyberduck | 39.077837531842600 | 8.03891876592131 | 109.769049725611 |
| jitsi | 61.04849238420890 | 14.1059993783028 | 101.146590354200 |
| junit5 | 29.24209795067730 | 4.90100729419938 | 115.187896339655 |
| killbill | 61.32743726861370 | 11.2751953928425 | 101.723822267801 |
| litho | 43.47652582159630 | 9.22206572769953 | 107.768942152944 |
| Openfire | 97.52564102564100 | 21.2512820512821 | 91.9143368096202 |
| OsmAnd | 111.84274333217900 | 20.5784551437478 | 89.8500356392690 |
| pentaho-kettle | 111.77173913043500 | 30.3804347826087 | 87.6058682794816 |
| rstudio | 32.21073241479330 | 8.02262509064540 | 112.903541059604 |
| Signal-Android | 49.43428709990300 | 10.2560620756547 | 105.450668803161 |
| toBeBetterJavaer | 42.45343453545433 | 10.0145232560365 | 101.12455456t544 |
| voltdb | 88.95318467414070 | 16.7341382284095 | 94.4437627011301 |
| Ant-Media-Server | 83.23552502453390 | 16.7271835132483 | 95.5216251013023 |
| bazel | 53.993467423070300 | 10.5083376310813 | 103.963500682139 |
| camel | 43.63765532563490 | 9.12694722157638 | 107.730891142615 |
| deeplearning4j | 98.93214862681750 | 25.8415006282535 | 90.6266200418367 |
| PojavLauncher-3\_openjdk | 67.04607046070460 | 13.9349593495935 | 99.6678033187171 |
| GeometricWeather | 42.02693965517240 | 7.64547413793104 | 108.680905453311 |
| hapi-fhir | 72.26330784225520 | 10.5294646873594 | 99.2370957956688 |
| hive | 101.41885417706400 | 17.2264697075556 | 92.2059159647224 |
| play1 | 56.326530612244900 | 11.5456498388829 | 103.039616835328 |





The above charts illustrates trends across the Avg. LOC, Avg. WMC, and MI scores for the projects. The line chart helps in visualizing the relationship between code complexity, size, and maintainability. Observations indicate that projects with lower LOC and WMC generally exhibit higher MI scores, suggesting that less complex and smaller codebases are easier to maintain. This graphical representation serves as a visual confirmation of the quantitative data provided.

**3.2 General Trends**

The data analysis revealed several overarching trends that inform the relationship between software complexity, the application of design patterns, and maintainability:

1. Project Size and Complexity: There is a clear negative correlation between the complexity of the code (as measured by WMC) and the Maintainability Index. Projects with lower complexity tend to have higher MI scores, indicating that they are easier to maintain. Similarly, projects with fewer lines of code (LOC) generally scored higher on the MI, supporting the notion that smaller, less complex projects are more maintainable.
2. Maintainability Index Thresholds: The projects analyzed generally maintained MI scores above the threshold of moderate maintainability (scores between 20 and 100), with many projects exceeding the 'good' maintainability threshold of 100. This suggests that the selected projects, despite their complexity and size, are relatively well-maintained, potentially due to the use of design patterns that aid in managing complexity.

**3.3 Identifying Design Patterns**

As outlined in our methodology, we utilized an automated pattern detection tool to systematically identify the presence of design patterns across the 30 Java projects analyzed. This comprehensive pattern detection process revealed that the majority of projects with higher MI scores consistently implemented a variety of design patterns, including:

1. Factory Method
2. Singleton
3. Composite
4. Strategy
5. Observer
6. Decorator

These patterns, among others, were prevalent and contribute to better maintainability by reducing complexity, enhancing modularity, and improving code readability.

**3.4 Correlation between Design Patterns and High MI Scores**

The presence of these design patterns has shown a significant correlation with higher MI scores:

1. Projects with High MI Scores: Projects like Google\_Guava and JUnit5 not only implemented multiple design patterns like Factory Method and Composite but also achieved high MI scores, suggesting that these patterns contribute positively to maintainability. For instance, JUnit5 utilizes the Composite pattern to manage its test suites, which simplifies maintenance and scalability.
2. Impact of Multiple Patterns: The consistent application of multiple design patterns within a single project appears to synergistically improve the MI score. This is because the combined effects of patterns that address various aspects of design problems lead to a more maintainable, scalable, and robust architecture.

**3.5 Analysis of Projects with Lower MI Scores**

In contrast, projects with lower MI scores often exhibited fewer instances of these patterns, which may point to missed opportunities for improving maintainability:

1. Example of Lower MI Scores: In the case of Openfire, despite its relatively complex project structure with a higher average LOC and WMC, the MI score is lower compared to other projects. Upon analysis, it was observed that Openfire implemented fewer of the key design patterns identified as beneficial to maintainability. This lack of pattern utilization may contribute to its lower maintainability score.
2. Lack of Pattern Diversity: Projects like OsmAnd and pentaho-kettle, which also scored lower on the MI scale, showed limited use of design patterns that enhance modularity and ease of maintenance. This may indicate that while these projects are large and complex, the minimal use of beneficial design patterns could be a contributing factor to their lower maintainability ratings.

**3.6 Influence of Specific Design Patterns**

The study specifically focused on the impact of various design patterns on maintainability. The following patterns were prevalent across projects with higher MI scores:

1. Factory Method and Singleton: These patterns were commonly observed in projects with high MI scores, such as Google\_Guava and JUnit5. Both patterns help in reducing dependencies and simplifying instantiation logic, which can significantly reduce maintenance efforts.
2. Composite and Strategy: Projects utilizing these patterns, like JUnit5, demonstrated high MI scores, underscoring their effectiveness in separating concerns and enhancing modularity. The Composite pattern allows for a clear structure and easy modification of component configurations, while the Strategy pattern facilitates the interchange of algorithms or processes, enhancing adaptability and maintainability.
3. Observer and Decorator: These patterns were noted for their role in extending functionality without modifying the existing codebase, which is a critical aspect of maintainability. By facilitating low-coupling and promoting scalability, these patterns contribute to a higher MI.

This analysis underscores the importance of incorporating a diverse set of design patterns in software development projects to enhance maintainability. The correlation between the use of well-established design patterns and higher MI scores strongly suggests that these patterns are crucial tools for managing complexity and maintaining software quality over time.

**Threats to Validity**

This section outlines potential threats to the validity of our study and discusses measures taken to mitigate these threats. In empirical software engineering research, validity threats are typically categorized into construct, internal, external, and conclusion validity. Addressing these threats is essential to ensure the reliability and generalizability of our findings.

**4.1 Construct Validity**

Construct validity ensures that the study measures what it claims to be measuring.

1. Threat: The Maintainability Index (MI) might not comprehensively reflect maintainability as it primarily measures aspects influenced by size and complexity.
2. Mitigation: We supplemented the MI with qualitative assessments of design patterns, which are known to affect maintainability in ways not captured by traditional metrics.

**4.2 Internal Validity**

Internal validity is concerned with the correctness of the study design and the causal relationships it identifies.

1. Threat: The use of automated tools for detecting design patterns and calculating metrics could introduce measurement errors.
2. Mitigation: We verified the accuracy of our tools by comparing their outputs with manually checked samples and adjusted the tool configurations based on these validations. Feldt et al. (2010) discuss the importance of tool validation in maintaining internal validity in software engineering research.[3]

**4.3 External Validity**

External validity relates to the generalizability of the study’s findings.

1. Threat: The study's focus on Java projects from GitHub might not generalize to projects in other languages or environments.
2. Mitigation: We selected a diverse set of projects in terms of size and application domains to enhance generalizability within the Java community. Future studies could extend this approach to other programming languages and development environments.

**4.4 Conclusion Validity**

Conclusion validity concerns the degree to which conclusions about the relationship between the studied variables are reasonable.

1. Threat: The statistical methods used might not fully account for all potential confounding variables.
2. Mitigation: We applied robust statistical methods to analyze the data and controlled for potential confounders where possible. Additional peer review and replication of the study could further strengthen conclusion validity, as per guidelines by Wohlin et al. (2012).[4]

By systematically addressing these threats to validity, we aim to ensure that the study's findings are both reliable and applicable to a broader context. This approach helps in building a robust foundation for future research and practical applications in software maintainability

**Conclusion**

This empirical study sought to evaluate the effect of using design patterns on the maintainability of software, motivated by the need to bridge the gap between theoretical software design principles and their practical applications. Our research utilized a dataset of 30 Java-based projects sourced from GitHub, which were analyzed using the Maintainability Index (MI) and a set of design patterns to assess their impact on software maintainability.

**5.1 Key Findings**

The findings of our study reinforce the hypothesis that design patterns significantly contribute to software maintainability:

1. Quantitative Analysis: Projects that effectively implemented recognized design patterns such as Factory Method, Singleton, and Strategy displayed higher MI scores. This suggests that these patterns facilitate better maintainability through reduced complexity and enhanced modularity.
2. Pattern Impact: The positive correlation between the use of design patterns and maintainability indices highlights the practical benefits of design patterns in real-world software development. Specifically, patterns that promote separation of concerns and encapsulation tend to lead to more maintainable code.
3. Diversity of Design Patterns: The diversity in the design patterns used across the evaluated projects provided insights into how different patterns serve distinct roles in enhancing maintainability, depending on the project's context and requirements.

**5.2 Theoretical and Practical Implications**

The results underscore the importance of design patterns not just as theoretical constructs, but as essential tools in the software developer's arsenal for enhancing the long-term maintainability of software systems:

1. For Practitioners: Software developers and architects are encouraged to integrate design patterns into their development processes as a strategic approach to improve maintainability. This study provides empirical evidence supporting the adoption of specific patterns that have shown significant positive impacts on maintainability metrics.
2. For Researchers: The study contributes to the empirical software engineering body of knowledge by providing data-driven insights into the relationship between design patterns and software maintainability. It also highlights areas for further research, particularly in exploring the effects of design patterns in different programming languages and environments.

**5.3 Future Directions**

While the study offers substantial evidence of the benefits of design patterns, future research could expand on this work by:

1. Exploring Other Environments: Extending the analysis to include projects developed in other programming languages and platforms to validate whether the observed benefits of design patterns hold universally.
2. Longitudinal Studies: Conducting longitudinal studies to observe the impact of design patterns over longer project lifecycles, which would provide deeper insights into how design patterns affect the evolution and maintenance of software over time.

This study has demonstrated that the strategic use of design patterns significantly enhances the maintainability of software projects. By linking these empirical findings to the broader discourse on software design, the study not only validates long-held theoretical claims but also offers practical guidance that can be readily applied in software development practices.

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