How Does API Migration Impact Software Quality and Comprehension? An Empirical Study

Hussein Alrubaye∗, Deema AlShoaibi∗, Mohamed Wiem Mkaouer∗, Ali Ouni†

∗Software Engineering Department, Rochester Institute of Technology, NY, USA
†ETS Montréal, University of Quebec, Montréal, QC, Canada
{hat6622, da3352, mwmvse}@rit.edu, ali.ouni@etsmtl.ca

Abstract—The migration process between different third-party software libraries is hard, complex and error-prone. Typically, during a library migration process, developers opt to replace methods from the retired library with other methods from a new library without altering the software behavior. However, the extent to which such a migration process to new libraries will be rewarded with an improved software quality is still unknown. In this paper, we aim at studying and analyzing the impact of library API migration on software quality. We conduct a large-scale empirical study on 9 popular API migrations, collected from a corpus of 57,447 open-source Java projects. We compute the values of commonly-used software quality metrics before and after a migration occurs. The statistical analysis of the obtained results provides evidence that library migrations are likely to improve different software quality attributes including a significantly reduced coupling, increased cohesion, and improved code readability. Furthermore, we release an online portal that helps software developers to understand the pre-impact of a library migration on software quality and recommend migration examples that adopt best design and implementation practices to improve software quality. Finally, we provide the software engineering community with a large scale dataset to foster research in software library migration.

I. Introduction

Prior studies show that software maintenance activities consume up to 70% of the total life-cycle cost of a typical software product [1]. One of the important software maintenance activities in modern software development is third-party library migration [2], [3]. In practice, library migration can be seen as the process of replacing a library with a different one, while preserving the same program behavior. The library migration process tends to be a manual, error-prone, and time-consuming process [4], [5], [6], [7], [8]. Hence, developers have to explore and understand the new library’s API, its associated documentation, and its usage scenarios in order to find the right API method(s) to replace in the current implementation belonging to the retired library’s API. As a consequence, developers often spend a considerable time to verify that the newly adopted features do not introduce any regression. Indeed, previous studies have shown that developers typically spend up to 42 days to migrate between libraries [9].

Unlike library upgrades, library migration typically requires more fine-grained code changes and refactorings, e.g., changing types of variables and parameters, renaming attributes and methods etc., since developers need to accommodate for the syntactic and semantic mismatch between the added and removed methods [2]. These refactoring changes may account for the overhead needed to fulfill the migration and adjust the existing software design to the newly introduced methods. Even if refactoring is perceived to be one of the best software engineering practices for restructuring code to improve its quality [10], the intention behind API-related refactoring operations might be different. Typically, API migration introduces a set of methods and objects with different lexicality and naming convention, which has to be integrated into the existing codebase terminology. That is, developers may refactor their code during library migration to help in the migration process and adapt to the new library context. Moreover, refactoring can have its impact on software design metrics (e.g., cohesion, coupling, etc.) [11] as well as code readability [12], [13], [14].

Various studies focused on analyzing the impact of API evolution on software quality in terms of change and bug-proneness [15], [16], [17], software usability and rating [18], [19]. Other studies focused on estimating the impact of API documentation on the library adoption and usability has been investigated in the literature [20], [21]. Moreover, recent studies attempted to identify traces of manually performed library migrations. They provide the community of a set of real-world migrations between popular Java libraries, in various open source projects [3], [5], [9].

The existing works reveal the importance of taking into account the software design characteristics when performing the migration to reduce maintenance costs. However, there is little knowledge on the impact of API migration, and its related refactoring changes, on the quality of software’s design as well as code com-
prehension and readability. As software systems evolve rapidly, there is a need for appropriate tools, reliable, and efficient techniques to support developers in replacing their deprecated library APIs with up-to-date ones, and maintaining/improving the quality of their software design.

To address the above-mentioned issues, we conduct a large-scale empirical study to assess the impact of library migration on both software design quality and code comprehension. We consider an existing dataset of 9 popular migrations between Java libraries, mined from 57,447 open-source Java projects [9]. Afterward, we shortlist all commits containing traces of method swaps, as part of any of considered migrations. We refine our dataset by untangling each commit to identify the specific code elements involved in the migration using program analysis. Then, for the selected code elements, we calculate the values of their corresponding design and readability metrics, before and after the migration. Finally, we statistically compare the variation of these values, to analyze whether the migration had a significant, positive, or negative impact on design quality and readability. To better understand the variation of these values, we use refactoring Miner [22] to extract the refactoring activities that were associated with the migration process. We finally associate a ranking score, to each migration trace, according to the extent to which it was able to improve the design and readability of the existing code. Furthermore, We survey 10 senior developers to assess the usefulness of the ranking score in providing better migration examples.

The paper is structured as follows: Section II unlocks the terminology that is used throughout the paper. Section III enumerates the studies relevant to our problem. Section IV shows our experimental methodology in collecting the necessary data for the experiments that are discussed in Section V. Finally, the conclusion and future work are highlighted in Section VII.

II. BACKGROUND AND TERMINOLOGY

This section presents definitions of the main concepts that are used throughout the paper. We first define the terminology used to characterize a library migration, then we provide the background information about structural and comprehension measures.

Migration Rule. A migration is denoted by a pair of a source (retired) library and a target (replacing) library, i.e., source → target. For example, easymock → mockito represent a migration rule where the library easymock is migrated to the new library mockito.

Method Mapping. A migration rule is a set of method mappings between the source and the target library. The mapping between methods is the process of replacing a least one method from the source library by one or multiple methods belonging to the target library.

Migration Refactoring. A refactoring operation applied in a commit in which a library migration occurs.

Refactoring is defined as the process of changing software system in such was that changes improve software quality and do not alter the software behaviour [23], [24]. Refactoring is one of the commonly-used techniques to improve software quality [10], [24]. There are different refactoring operations that could be used to improve software quality such as a change in parameter types, move attributes/methods, rename variables/parameter-s/attributes/methods/classes, extract methods, extract classes, etc [24].

While object oriented (OO) software quality metrics are measurable from the codebase and formally defined in the literature [11], code readability is still a human judgment of how easy the code to understand, and a readable code facilitates its maintainability and comprehension [12], [13], [14]. We partcularly focus on the following design metrics:

Coupling. Measure the level of relationship between modules [25]. While designing the software, low coupling is desirable (i.e., less dependency between modules). In this case, we also used one metric to compute it, i.e., Coupling Between Objects (CBO). The higher the CBO, the higher the class coupling.

Cohesion. Measure the level of relationship within module [25]. While designing the software, high cohesion is desirable (i.e., strong interaction between code

---

1) We release an online portal that showcases real-world migration fragments, with their corresponding positive or negative impact on coupling, cohesion, and readability.

2) We propose a ranking score, that we label Migration Quality Score (MQS), for recommending migration examples that ensure better software quality and comprehension.

3) We survey with senior software engineers at an outstanding company to evaluate MQS’s ability to recommend high-quality migration examples for 9 popular migrations. Findings show that MQS effectively recommends high-quality migration examples.

While designing the software, low coupling is desirable (i.e., less dependency between modules). In this case, we also used one metric to compute it, i.e., Coupling Between Objects (CBO). The higher the CBO, the higher the class coupling.

Cohesion. Measure the level of relationship within module [25]. While designing the software, high cohesion is desirable (i.e., strong interaction between code

---

1) We release an online portal that showcases real-world migration fragments, with their corresponding positive or negative impact on coupling, cohesion, and readability.

2) We propose a ranking score, that we label Migration Quality Score (MQS), for recommending migration examples that ensure better software quality and comprehension.

3) We survey with senior software engineers at an outstanding company to evaluate MQS’s ability to recommend high-quality migration examples for 9 popular migrations. Findings show that MQS effectively recommends high-quality migration examples.

The paper is structured as follows: Section II unlocks the terminology that is used throughout the paper. Section III enumerates the studies relevant to our problem. Section IV shows our experimental methodology in collecting the necessary data for the experiments that are discussed in Section V. Finally, the conclusion and future work are highlighted in Section VII.

II. BACKGROUND AND TERMINOLOGY

This section presents definitions of the main concepts that are used throughout the paper. We first define the terminology used to characterize a library migration, then we provide the background information about structural and comprehension measures.

Migration Rule. A migration is denoted by a pair of a source (retired) library and a target (replacing) library, i.e., source → target. For example, easymock → mockito represent a migration rule where the library easymock is migrated to the new library mockito.

Method Mapping. A migration rule is a set of method mappings between the source and the target library. The mapping between methods is the process of replacing a least one method from the source library by one or multiple methods belonging to the target library.

Migration Refactoring. A refactoring operation applied in a commit in which a library migration occurs.

Refactoring is defined as the process of changing software system in such was that changes improve software quality and do not alter the software behaviour [23], [24]. Refactoring is one of the commonly-used techniques to improve software quality [10], [24]. There are different refactoring operations that could be used to improve software quality such as a change in parameter types, move attributes/methods, rename variables/parameter-s/attributes/methods/classes, extract methods, extract classes, etc [24].

While object oriented (OO) software quality metrics are measurable from the codebase and formally defined in the literature [11], code readability is still a human judgment of how easy the code to understand, and a readable code facilitates its maintainability and comprehension [12], [13], [14]. We partcularly focus on the following design metrics:

Coupling. Measure the level of relationship between modules [25]. While designing the software, low coupling is desirable (i.e., less dependency between modules). In this case, we also used one metric to compute it, i.e., Coupling Between Objects (CBO). The higher the CBO, the higher the class coupling.

Cohesion. Measure the level of relationship within module [25]. While designing the software, high cohesion is desirable (i.e., strong interaction between code
elements in a module) since this target helps in fostering code maintainability. We used one metric to assess the cohesion of classes, i.e., the normalized Lack of Cohesion of Methods (LCOM). We have selected the normalized LCOM metric as it has been widely recognized in the literature [26], [27] as being the alternative to the original LCOM, as the latter addresses its main limitations (misperception of getters and setters, etc.). The lower the LCOM, the higher the class cohesion.

**Complexity.** A developer should reduce the complexity of the software to reduce maintenance time and efforts. Five complexity and volume metrics are used to compute this quality attribute, namely, the Cyclomatic Complexity (CycC), the Line of Code (LOC), the Line with Comments (CLOC), the Ratio of Comment Lines to Code Lines, and the Number of Blank Lines. Normally, higher values of these metrics indicate a higher of class complexity [11].

### III. Related Work

This section discusses the literature relevant to this work which can be divided into three main categories (i) library API recommendation, (ii) library migration, and (iii) empirical evaluation of software quality and comprehension.

#### A. Library API recommendation

Several recent studies proposed different API recommendation techniques based on the context of usage. Most of the API recommendation techniques are based on results returned by web search engines and crowd-sourcing, as well as the recommendation of relevant functions, was the focus of multiple studies [28], [29]. McMillan et al. [30] proposed an approach, named Portfolio, that consists of a search engine to model the developer’s behavior then looks for relevant functions based on (i) call graph similarity, and (ii) querying open-source projects using natural language processing. Zhong et al. [31] proposed another approach called MAPO to select API usage patterns and then extracts common sequences that can be used to transform code snippets and make recommendations automatically. CLAN was introduced later by McMillan et al. [32] and based on calculating method APIs behavioral similarity by comparing API call-graphs. Software libraries recommendation has been recently formulated as an optimization problem by Ouni et al. [33] using multi-objective search based on NSGA-II [34] to find the best trade-off between maximizing the coverage and similarity between libraries while reducing the number of recommended libraries.

#### B. Mining software quality and comprehension

Several studies focused on understanding how developers perceive API related method changes. In the context of library updates, many studies have been proposed to capture the needed changes on the client source code applied along with API migration [35], [36], [37], [38]. Most of the existing approaches use textual similarity between the structures and method signatures as a basic technique to identify identical methods between multiple library versions.

Pandita et al. [39] recommend API mapping between C# and Java using the same API, different programming languages. He detects method mappings between a given source and a target library by automatically discovering possible method mappings across their APIs, using text mining on the functions textual descriptions. Their work was extended to include temporal constraints [40] and to compare text mining between various IR techniques. A dynamic analysis was also used by Gokhale et al. [41] to develop a technique to infer possible mappings between the APIs of Java2 Mobile Edition and Android graphics.

Alrubaye et al. [6] introduced a mining approach that extracts existing instances of library method replacements that are manually performed by developers for a given library migration to automatically generate migration patterns in the method level. Thereafter, the proposed approach combines the mined method-change patterns with method-related lexical similarity to accurately detect mappings between replacing/replaced methods. Results indicate that substitution algorithm approach significantly increases the accuracy of mining method-level mappings by an average accuracy of 12%, as well as increasing the number of discovered method mappings, in comparison with existing state-of-the-art studies.

#### C. Empirical evaluation of software quality and comprehension

Recent empirical studies revisited the relationship between code changes and quality from a more developer-focused perspective. For instance, Pantiuchina et al. [26] found that there is a misperception between various popular metrics, such as coupling and cohesion, and what developers actually consider to be an improvement in their source code. Their findings show that, although developers do explicitly mention their intention in improving structural metrics, such as complexity, coupling and cohesion, the actual code changes that they perform does not necessarily improve their metrics. Similarly, Fakhoury and her colleagues [42] have analyzed 548 commits where their developers explicitly state in their messages that they are performing readability improvements, by measuring the state-of-the-art readability metrics, on the source code, before and after committing the code changes. Similarly to [26], Fakhoury et al. found no significant correlation between the values and so the current existing readability metrics is not in line with what developers consider to be an improvement in code comprehension. Yet, their study largely inspired us to
challenge the readability of code changes performed by developers during the migration process.

Our study builds on top of previous works, in the nature of its empirical setup, as we use a set of extracted commits, measure their impact on structural and comprehension metrics, and we perform statistical analysis to draw our findings. Besides targeting a different problem, our study differs from these previous studies, in the way we select our analyzed commits. Previous studies use String matching to filter out commits, while the dataset we use was constructed by finding real-world migration performed by developers and their actual mappings in the source code, regardless of whether developers do mention it explicitly in their commit messages or not. Despite these differences, we are also interested in re-challenging structural and readability metrics, on their ability to capture the side effects of the migration related code changes. Moreover, our study aims to complement existing studies by empirically investigating whether quality matters for developers, besides the correctness of migrated code. We also want to particularly raise the awareness of software engineering practitioner and researchers to the importance of considering the side effects of their proposed techniques on software quality and code comprehension.

IV. Empirical Setup

A. Research Questions

Our study is driven by the following research questions:

RQ1. (Design Improvement) What is the impact of library migration on the quality of software design?

To answer this research question, we assess the impact of library migration on software design quality, in terms of complexity, coupling and cohesion, widely popular structural metrics [43], and previously used in similar empirical studies [27], [26]. For each analyzed source file in the dataset (that we detail later in the next subsection), we measure the value of its coupling and cohesion before and after the migration. As we aggregate all values before and after the migration, we observe the variation in the aggregated values to investigate whether the migration had a positive or negative impact on design quality.

RQ2. (Code Readability) Does migration improve the code readability?

Similarly to RQ1, we consider popular state-of-the-art readability tools and metrics [14], [44]. For each metric, we measure its pair values in the dataset files, before and after the migration, and then we analyze the values for statistical significance.

RQ3. (Refactoring Operations) What types of refactoring changes do developers perform during library migration?

We explore, in this research question, design-related change patterns, observed across various migrations. We aim at understanding what are the most solicited refactoring operations that facilitate the integration of the target API methods.

RQ4. (Quality Recommendation) Can we leverage design and readability metrics to recommend better code examples for migration?

Since there are multiple code fragments, belonging to various projects and containing the same mappings, we
Table I: Dataset overview.

| Property                  | # of instances |
|---------------------------|----------------|
| # unique migrations       | 9              |
| # projects                | 57,447         |
| # Classes involved in migration | 36,023       |
| # unique mappings         | 9,380          |
| # refactoring operations  | 3,579          |

design a recommendation-based ranking method that aggregates various quality metrics. Our method ranks the collected code fragments based on the extent to which they preserve the design coherence and improve the code comprehension. We then perform a qualitative study with 10 senior developers to evaluate the usefulness of our recommendation-based ranking method.

B. Data Collection

Figure 1 provides an overview of our study workflow. We use an existing corpus of manually curated method mappings, extracted from 57,447 GitHub projects that underwent migrations between different third-party Java libraries [9]. We start by extracting all commits containing method replacements (manually annotated in the dataset). Then, we label them migration commits. Each migration commit contains at least one or multiple mappings, i.e., fragments of code containing one or multiple removed methods, being replaced with one or multiple added methods, along with other code changes that may or may not be related to the migration. Since any code change, non related to migration represents a noise for this study, we only consider files containing migrations fragments in each migration commits. We notice that some migrations are instant i.e., all method replacements are located in the same commit, but in multiple source files, and some migrations are delayed, i.e., method replacements are scattered across multiple commits.

The data collection process has analyzed commits belonging to a diverse set of 57,447 projects, all belonging to the original dataset [9]. We have identified 36,023 classes, each contains at least one mapping. We also enumerated 9,380 unique mappings, already showcased in the dataset’s website. We identified 3,579 refactoring operations that are associated with these mappings. We provide our collected data for replication and extension online.

C. Metrics Measurement

1) Structure and size metrics: To collect the design metrics, we use Scitools Understand, a static analysis framework that captures a variety of structural metrics, across languages such as C++ and Java. Based on the computed metrics values, we can calculate the effect of migration-related changes on the system design. In particular, we analyze the following size and structure metrics: Coupling Between Objects (CBO), normalized Lack of Cohesion (LOM), and Cyclomatic complexity.

Since each source file may contain multiple migration fragments, and since we only care about these specific files, we calculate metrics only for these fragments and then we average them to construct one value per file. In other terms, each data point in our analysis is a file with an average metric value.

2) Code readability metrics: Source code readability is one of the important aspects of software engineering. Several studies have been focusing on the automation of its approximation through deep static analysis. In this context, we measure code readability during the migration process using two state-of-the-art metrics, proposed by Buse and Weimer [14], and Scalabrino et al. [44]. We deploy both metrics as they were widely-employed in recent empirical studies [26], [42], and because they address different readability aspects. On the one hand, Buse and Weimer’s Readability metric (BWR) combines the source code size characteristics to approximate its readability. On the other hand, Scalabrino et al.’s Readability metric (SR) does not only look at the structural characteristics of code, and adds another lexical dimension, in which it considers more linguistic properties such as comments consistency with the source code and its coherence etc. Both metrics generate a score that, the higher it is, the better is the readability of the code.

Similarly to structural metrics, each data point in our analysis represents an average readability score per source file.

3) Refactoring operations collection: To extract the refactoring history of the selected commits, we use Refactoring Miner [45], an accurate state-of-the-art tool that can detect refactoring operations that are applied in the development history of a Java project. Refactoring Miner parses the source code in each commit, and returns a summary of applied refactoring operations such as a change in parameter type, moves attribute, renames attribute, renames parameter, renames method, renames variable, extracts class, etc. We selected this tool because of its high accuracy [22], [46] (precision of 98%, and recall of 87%), and because it is designed to mine refactorings from commit history, which perfectly matches our study context.

After applying these tools on all predefined mappings commits, before and after the migration, we generate a dataset that contains, for each commit, its associated code fragments, structural and readability metrics pairs of values, any detected refactoring operation(s). We then use this dataset as a base of examples that we rank according to how much they improve quality and comprehension. We detail our proposed ranking model in the following Section IV-D.
D. Ranking Model

The migration dataset [9] contains, for each migration rule, e.g., easymock to mockito, several commits, extracted from various projects, containing similar mappings. Therefore, for the same mapping, there are various real-world examples of how a deprecated method has been replaced with one or multiple replacing methods. Although these examples exhibit similar sets of removed/added methods, they differ in their overhead in the software design, since the migration process is subjective [3], [5], [8], and developers may perform different types of code changes to perform the same type of migration. Moreover, as maintaining a good quality of the source code, in terms of design and readability is critical for the code longevity, our aim is to favor the recommendation of source code migration examples that correctly execute the migration while also maintaining, or improving the current client code quality. To do so, we simply leverage the existing metrics, previously explored in Section IV-A, and combine them into an overall Mapping Quality Score (MQS). For each given migration in the dataset, we loop through all its mappings, for each mapping, we locate all its instances in the course code (inst). Then, for each instance, we calculate its MQS, and finally, we rank them on a descendent order, to favor examples with the highest quality improvement. Formally, we calculate the MQS as follows:

$$MQS(inst) = \sum_{i=1}^{5} W_i^{MQS} \cdot \varphi_i(inst)$$  \hspace{1cm} (1)

where MQS represents the weighted sum of all values \(\varphi_i\), and \(i\) varies according to the number of metrics used. The term \(\text{inst}\) denotes code instances to be ranked for a given mapping.

Since the combined metrics do not belong to the same scale, we normalize them using \textit{min-max normalizer} that linearly rescales every metric value to the [0,1] interval. Rescaling in the [0,1] interval is done by shifting the values of each feature \(x\) so that the minimal value is 0, and then dividing by the new maximal value (which is the difference between the original maximal \(\max(x)\) and minimal \(\min(x)\) values).

Moreover, since not all metrics are to be maximized, we transform all of them to be minimized using the duality principle. For example, since the lower are the values of coupling, the better they are, we maximize the complement of the normalized value of coupling, i.e., \(\varphi_{CBO} = (1-z(CBO(src)))\), where \(z\) returns the min-max normalized value.

As an illustrative example, we observe in Figure 1 that for a given mapping between createStrictMock, belonging to the removed library easymock, and mock, belonging to mockito, 4 instances are being shown and recommended as migration examples. Note that each example contains a link to the actual location of the code on GitHub. The examples have been ranked according to their MQS. For instance, the first example has the highest MQS of 2.475, while the second example has an MQS of 2.239.

Note that the normalization was restricted to the MQS calculation, we still use the actual raw values of the metrics for the results, which are detailed in the following sections. Also note that we weights for the actual MQS score are by default equal to 1 i.e., for this study, we consider all metrics to be equally important, and thus, this can be improved, if any metric has been found to be more influential than others in this context of API migration.

V. Results

This section details the results of our empirical setup to answer the research questions, previously elaborated in Section IV.

### A. RQ1. (Design Improvement) What is the impact of library migration on the quality of software design?

Figure 2 outlines the box plots of the values, for each of the structural metrics, calculated before and after the migration. To better understand the statistical significance of the observed results, we setup our statistical analysis as follows: for each metric, we cluster its values according to whether it was measured before or after the migration. We apply this to each code fragment. As a result, we create two groups of equal size, each containing measurements of the same metric before and after the migration. Then, we use the Wilcoxon signed rank test, since these groups are dependent (measurement on the same code fragments), to evaluate the significance of the difference between the values, in terms of their mean.

Our Null hypothesis indicates no variation in the metric values of pre- and post-migrated code elements. In contrast, the alternative hypothesis advocates for a variation in the metric values. In this research question, a decrease in the mean values is considered desirable (i.e., an improvement in design quality). Additionally, the variation between values of both sets is considered significant if its corresponding p-value is less than 0.05 (a confidence level of 95%). We deploy the same statistical analysis for RQ2 as well, but with a difference in the

| Metric   | p-value  |
|----------|----------|
| LCOM     | 1.06 × 10^{-75} |
| CBO      | 8.11 × 10^{-148} |
| CycC     | 4.78 × 10^{-131} |
| BWR      | 3.95 × 10^{-62}  |
| SR       | 3.40 × 10^{-12}  |
| Refactoring Operations | 0.013  |
Figure 2: Box plots of CBO, LCOM, and average CycC values, extracted from migrated code fragments, before and after the migration (lower values are better).

interpretation, since for readability metrics, an increase in mean value is considered desirable.

As can be seen in the Figure 2, for the coupling between objects metric (CBO), we clearly notice a general trend of values being significantly decreased, just after the migration. The mean CBO value has decreased from 2.047 to 1.884 (p-value < 0.05), and the upper quartile has become significantly lower while decreasing from 2.147 to 1.955. Interestingly, we also observe from the figure a similar trend for the Lack of Cohesion of Methods metric (LCOM), since its mean value has gone from 0.548 to 0.482 (p-value < 0.05). We also notice a drop in the lower quartile, going from 0.460 to 0.370.

As for the average Cyclomatic complexity, there is a slight decrease in the upper quartile, varying from 2.146 to 2.050, but the mean value has decreased from 1.593 to 1.505 (p-value < 0.05).

Figure 3: Illustrative example of a code migration from log4j to slf4j, with a positive impact on coupling.

To better understand the observed results, we manually analyze few random instances. Figure 3 illustrates a code fragment example of such migrations, extracted from Github. In this fragment, the methods addPackage with addClasses, belonging to the library log4j, is being replaced with the method addClasses, from slf4j. We can observe the difference in the used parameters between the replaced and replacing methods. More precisely, addPackage with addClasses have a CBO of 4, while addClasses only have a CBO of 3, which did improve the overall CBO of all methods by adopting this newly deployed method.

Figure 4: Illustrative example of a code migration from async-http-client to httpclient, with a positive impact on cohesion.

Another interesting example, shows how the newly introduced object DefaultHttpClient does not rely on any parameter, unlike the retired object HttpClient whose constructor is initialized with connectionManager. Therefore, the new object is more cohesive and it reduces the lack of cohesion of the system.

Summary for RQ1. Our empirical analysis has shown that APIs migration exhibit a positive impact on the software’s design quality, in terms of complexity, coupling and cohesion.

B. RQ2. (Code Readability) Does migration improve the code readability?

Figure 5 outlines the boxplots of the values, for each of the readability metrics, calculated before and after each API migration.

For the BWR [14] metric, we observe an improvement in its values. In particular, the mean BWR [14] value has increased from 0.474 to 0.482 (p-value < 0.05). Similarly, the lower and the upper quartiles have slightly increased respectively from 0.316 to 0.329, and 0.579 to 0.587. As for the second readability metric, namely SR [44], the improvement is more significant since its mean value exhibits an increase from 0.568 to 0.603 (p-value < 0.05). The increase is also seen in the lower quartile, going from 0.461 to 0.484, whereas the upper quartile exhibits a slight decrease from 0.709 to 0.706.

If we take deeper look into the code example, illustrated in Figure 6, we notice that the developer just moved from using the method put, from json to the method addProperty, from gson. Note that the developer did not perform any additional activities; however the BWR [14] improved from 0.0013 to 0.0023 since the method name addProperty has better readability score than put, as shown in the console output of BWR [14] in Figure 6.

9https://github.com/anthonydahanne/ReGalAndroid/commit/64105cc9e3e7459b9d8299a102ca5d9262b9f9
10https://github.com/groupon/Selenium-Grid-Extras/commit/4d9b9a8e3a509e7a27296eb94eac88b5a1b51
Summary for RQ2. API migrations do improve code readability, as both BWR [14] and SR [44] readability metrics experience a significant increase when comparing code fragments before and after the migration.

C. RQ3. (Refactoring Operations) What types of refactoring changes do developers perform during library migration?

When developer performs a migration between two libraries, he/she may need to change/refactor the client code around the retired library methods to migrate from the old to the new library such as renaming variables/parameters, changing types, moving code elements, etc. As our goal is to assess whether developers change and refactor differently when they migrate, we need to compare also the refactoring activities in other regular commits in which there was no APIs migration performed, to get appropriate statistical analysis. In other terms, we need to evaluate whether the changes and refactoring are related to the migration or any other factor. Indeed, causal inference stems from the social sciences and explores cause and effects as its main concern. In economometrics, Difference-In-Differences (DID) methods are one of the key analytical elements for causal inference [47]. We adopted the DID method in our analysis to statistically visualize actual and counterfactual scenarios, thereby enabling a causality analysis. DID consists of comparing two groups, one with the intervention (i.e., migration) and one without it.

Indeed, DID depends on the common trends assumption [47] based on the selection of an appropriate control group. We selected our control group (i.e., code fragments that did not exhibit API migration) using the propensity score matching since it is a popular matching technique. In particular, we used the well-known nearest neighbor matching algorithm in propensity score matching based on the following characteristics: the subsystem, the source file size, the contributor who applied the refactoring, and the period of time (the same month). A total of 3,579 refactoring operations were identified as a control group, to have an equal group to our current dataset size as described in Table I.

Figure 7 shows compassion between refactoring operations that happen during migration activities with the refactoring of our control group in terms of the percentage of applied refactoring. Overall, we found that the distribution of refactoring in migration commits
and other commits are statistically different ($p-value = 0.013$), as reported in Table II. This finding indicates that developers do refactor and change their code differently when they perform API migration. In particular, as can be seen in Figure 7, we find that developers are likely to change the parameter type, rename variables and rename attributes when they migrate their APIs. The results make sense because the developer may refactor her/his client code around the method of the retired library to map the code and match the requirements of the method from the new library. Such refactoring may facilitate the migration by adjusting the existing code elements to match the signature of the added method(s). Indeed, this explains the high rate of type change refactoring, being performed along with various rename refactoring to bridge the lexical gap between the existing codebase and the introduced API.

Moreover, as can be seen in the figure, while in regular refactoring commits, developers most likely to apply extract method, rename method, and move class/attribute/method refactoring, the refactoring practices has changed in migration commits. As an illustrative example, Figure 8 shows a sample of migration code for developer changed method parameter type from JSONObject to JsonObject, while refactoring the code to migrating from method add that belongs to json to the method addProperty that belongs gson.

**Figure 8:** Illustrative example of a code migration from json to gson, being supported by applying a change parameter type refactoring.

---

**Summary for RQ3.** Developers change the way they refactor their code during API migrations by focusing more on applying refactoring operations that facilitates the integration of the added methods. We highlight operations such as change parameter type, rename parameter and rename attribute.

---

**D. RQ4. (Quality Recommendation)** Can we leverage design and readability metrics to recommend better code examples of migration?

To evaluate our ranking model based on the structural and readability metrics, we conducted a qualitative analysis with 10 senior developers from an outstanding software development company. All the participants volunteered to participate in the experiment and were familiar with Java programming, Maven ecosystem, and API usage. The experience of these participants with Java development is 10+ years. Prior to the experiment, the participants were provided with a 30-minutes tutorial on the tool usage and the experiment process. Each participant were provided with 10 code fragments to perform 10 migration tasks between libraries including easymock to mokito, and json to gson. Then, for each of the migration tasks, the developer runs our migration code examples tool that returns a list of examples but exposed to the developers at a random order (at least for our experimental study to avoid biased selection from a ranked list). Then, the developer reviews all the returned examples and picks the top-3 examples that fit her/his preferences and the quality of the examples.

Figure 9 reports the survey results, where the x-axis represents the index of example($k$) in the ranked list, and the y-axis represents the number of times an example@$k$ has been chosen by a developer as their top choice, divided by all choices. In other terms, the y-axis percentage of developers’ choice of an example whose rank is $k$. For instance, the value @$k = 1$ is the percentage of how many times the example number one in the ranked list was chosen at the best example.

According to Figure 9, we could see that 59% of developers agreed that the first recommended example is the best example. If we allow the top-2 ranked examples ($k <= 2$), our recommendation already captures 80% of developers’ choices, which also improves further to become 94% for top-3 ranked examples ($k <= 3$).

We can conclude that our ranking model efficiently recommends what developers consider to be their decision if they are requested to perform the migration.

---

**Figure 9:** Percentages of the match between developers choices and the example@$k$.  

---

11https://github.com/groupon/Selenium-Grid-Extras/commit/4d9bada8aeb5b09607a2797fe6c90ca0b95a1b51 in FirstTimeRunConfig.java
VI. THREATS TO VALIDITY

We report, in this section, potential factors that can threaten the validity of our empirical study.

A. Internal Validity.

Our empirical analysis is mainly threatened by the accuracy of the migration dataset. Since our assumption that all studied commits carried at least one migration, any intruding files would be considered as noise to our analysis. We did not perform any rigorous verification concerning the correctness of the dataset, but we did perform various manual checks when gathering the files for statistical analysis and for qualitatively analyze our findings, and we did not notice any single case where the file we were investigating did not contain at least one migration trace.

The second main threat to the validity of our work is the choice of the metrics used in this study. We have chosen coupling, cohesion, and complexity, as being representative to design quality and popular metrics, being used in similar empirical studies [48], [27].

The non diverse set of developers, along with the randomness in assigning them the examples, has a direct impact on the results. The choice of experienced and volunteers was to reduce the effect of non interest to the problem resolution. Developers were genuinely interested to support the work, and they were aware of it being potentially published for the community.

B. Construct validity

Threats to construct validity describe concerns about the relationship between theory and observation and, generally, this type of threat is mainly constituted by any errors related to measurements. More precisely, any error in the used tools directly impacts the correctness of our findings. For calculating metrics, we have used popular frameworks and libraries such as Refactoring Miner [45] and Understand. For Refactoring Miner, previous studies [45], [22] report that Refactoring Miner has high precision and recall scores, compared to other state-of-the-art refactoring detection tools. Similarly, readability tools have been used in previous similar studies [26], [42], and based on our own humble experience, we did not notice any anomaly while using them.

Moreover, in this study, we did not differentiate between instant and delayed migrations, by combining their results. This may not have allowed to fully understand the difference between both, especially that the instant migration is performed faster than the delayed migration, which may hypothesize that developers may have focused on the correctness of their migrated code, rather than optimizing the design of their system. This remains one of our main future experiments.

C. External validity

Threats to external validity are connected to the generalization of the obtained results. Our empirical study was limited to only open source Java projects. However, we constrained by the tools we use to collect the metrics, and besides Understand, others can only process Java source code. Thus, only the first research question can be extended across languages, if there is such a dataset because the one we have used is also limited to Java libraries.

VII. CONCLUSION AND FUTURE WORK

In this paper, we conducted a large scale empirical study to investigate the impact of software migration between third-party libraries on code quality and comprehension. Our qualitative and empirical analysis indicate that library migrations have a positive impact on software’s design, in terms of coupling and cohesion. We also experiment their effect on two state-of-the-art code readability metrics, and we observe an improvement in both metrics. We observed multiple factors that explain the improvement, including the typical better naming conventions and more cohesive API methods. We also noticed a particular refactoring activity that aims to facilitate the migration by adjusting the existing code elements to match the signature of the added method(s). This explains the high rate of type change migrations, being performed simultaneously with the addition of new methods, along with various rename refactorings to bridge the lexical gap between the existing codebase and the introduced API. Finally, we leverage structural and readability metrics to define a ranking score for migration examples. To evaluate the effectiveness of our ranking, we surveyed developers to see whether our top recommended examples would match what developers consider to be the best choice. Results show that our top-1 recommended example achieves an agreement of 59%.

These factors drive our future work. We plan on further leveraging API contextual information to recommend better APIs for usage, with respect to a given code fragment. We also plan on extending the structural metrics used to characterize software design quality, such as including the weighted method per class, response for a class, class stability, and depth of inheritance tree.

REFERENCES

[1] Barry Boehm and Victor R Basili. Software defect reduction top 10 list. Foundations of empirical software engineering: the legacy of Victor R. Basili, 426(37):426-431, 2005.
[2] Cedric Teyton, Jean-Remy Falleri, and Xavier Blanc. Mining library migration graphs. In Reverse Engineering (WCRE), 2012 19th Working Conference on, pages 289–298. IEEE, 2012.

[3] Cedric Teyton, Jean-Remy Falleri, and Xavier Blanc. Automatic discovery of function mappings between similar libraries. In In Reverse Engineering (WCRE), 2013 30th Working Conference on, pages 192–201. IEEE, 2013.

[4] Bradley E Cossette and Robert J Walker. Seeking the ground truth: a retrospective study on the evolution and migration of software libraries. In Proceedings of the ACM SIGSOFT 20th International Symposium on the Foundations of Software Engineering, page 55. ACM, 2012.

[5] Cedric Teyton, Jean-Remy Falleri, Marc Palyart, and Xavier Blanc. A study of library migrations in java. Journal of Software: Evolution and Process, 26(11):1030–1052, 2014.

[6] Hussein Alrubaye and Mohamed Wiem Mkaouer. Automating the detection of third-party java library migration at the function level. In Proceedings of the 28th Annual International Conference on Computer Science and Software Engineering, pages 60–71. IBM Corp., 2018.

[7] Raula Gaikovina Kula, Daniel M German, Ali Ouni, Takashi Ishio, and Katsuro Inoue. Do developers update their library dependencies? Empirical Software Engineering, 23(1):384–417, 2018.

[8] Hussein Alrubaye and Mohamed Wiem. Variability in library evolution. Software Engineering for Variability Intensive Systems: Foundations and Applications, page 295, 2019.

[9] Hussein Alrubaye, Mohamed Wiem Mkaouer, and Ali Ouni. On the use of information retrieval to automate the detection of third-party java library migration at the method level. In Proceedings of the 27th International Conference on Program Comprehension, pages 347–357. IEEE Press, 2019.

[10] Konstantinos Strogylos and Diomidis Spinellis. Refactoring—does it improve software quality? In Fifth International Workshop on Software Quality (WosQ'07: ICSE Workshops 2007), pages 10–10. IEEE, 2007.

[11] Shyam R Chidamber and Chris F Kemerer. A metrics suite for object oriented design. IEEE Transactions on software engineering, 20(6):476–493, 1994.

[12] Spencer Rugaber. The use of domain knowledge in program understanding. Annals of Software Engineering, 9(1-2):143–192, 2000.

[13] Krishan K Aggarwal, Yogesh Singh, and Jitender Kumar Chhabra. An integrated measure of software maintainability. In Annual Reliability and Maintainability Symposium, 2002 Proceedings (Cat. No. 02CH37318), pages 235–241. IEEE, 2002.

[14] Raymond P Bunderson and Westley R Weimer. Learning a metric for code readability. IEEE Transactions on Software Engineering, 36(4):546–558, 2010.

[15] Daniele Romano, Paulius Raita, Martin Pinzger, and Foutze Khomh. Analyzing the impact of antipatterns on change-proneness using fine-grained source code changes. In 2012 19th Working Conference on Reverse Engineering, pages 437–446. IEEE, 2012.

[16] Tyler McDonnell, Baishakhi Ray, and Miryung Kim. An empirical study of api stability and adoption in the android ecosystem. In 2013 IEEE International Conference on Software Maintenance, pages 70–79. IEEE, 2013.

[17] Mijung Kim, Jaechang Nam, Jaehyuk Yoon, Soonhwan Choi, and Sung hun Kim. Remi: defect prediction for efficient api testing. In Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering, pages 990–993. ACM, 2015.

[18] Mario Linares-Vásquez, Gabriele Bavota, Carlos Bernal-Cárdenas, Massimiliano Di Penta, Rocco Oliveto, and Denys Poshyvanyk. Api change and fault proneness: a threat to the success of android apps. In Proceedings of the 2013 9th joint meeting on foundations of software engineering, pages 477–487. ACM, 2013.

[19] Gabriele Bavota, Mario Linares-Vasquez, Carlos Eduardo Bernal-Cardenas, Massimiliano Di Penta, Rocco Oliveto, and Denys Poshyvanyk. The impact of api change-and fault-proneness on the user ratings of android apps. IEEE Transactions on Software Engineering, 41(4):384–407, 2014.

[20] Martin P Robillard and Robert Deline. A field study of api learning obstacles. Empirical Software Engineering, 16(6):703–732, 2011.

[21] Stefan Endrikat, Stefan Hanenberg, Romain Robbes, and Andreas Stefik. How do api documentation and static typing affect api usability? In Proceedings of the 36th International Conference on Software Engineering, pages 632–642. ACM, 2014.

[22] Nikolaos Tsantalis, Matin Mansouri, Laleh M Eshekevari, Davood Mazinanian, and Danny Dig. Accurate and efficient refactoring detection in commit history. In Proceedings of the 40th International Conference on Software Engineering, pages 483–494. ACM, 2018.

[23] William F Opdyke. Refactoring object-oriented frameworks. 1992.

[24] Martin Fowler. Refactoring: improving the design of existing code. Addison-Wesley Professional, 2018.

[25] Wayne P. Stevens, Glenford J. Myers, and Larry L. Constantine. Structured design. IBM Systems Journal, 13(2):115–139, 1974.

[26] Jevgenija Pantuchchina, Michele Lanza, and Gabriele Bavota. Improving code: The (mis) perception of quality metrics. In 2018 IEEE International Conference on Software Maintenance and Evolution (ICSME), pages 80–91. IEEE, 2018.

[27] Alexander Chávez, Isabella Ferreira, Eduardo Fernandes, Diego Cedrim, and Alessandro Garcia. How does refactoring affect internal quality attributes?: A multi-project study. In Proceedings of the 31st Brazilian Symposium on Software Engineering, pages 74–83. ACM, 2017.

[28] Ferdian Thung, David Lo, and Julia Lawall. Automated library recommendation. In 2013 20th Working Conference on Reverse Engineering (WCRE), pages 182–191. IEEE, 2013.

[29] Ferdian Thung, Richard J Oentaryo, David Lo, and Yuan Tian. Webapirec: Recommending web apis to software projects via personalized ranking. IEEE Transactions on Emerging Topics in Computational Intelligence, 1(3):145–156, 2017.

[30] Collin Mcmillan, Denys Poshyvanyk, Mark Grechankin, Qing Xie, and Chen Fu. Portfolio: Searching for relevant functions and their usages in millions of lines of code. ACM Transactions on Software Engineering and Methodology (TOSEM), 22(4):37, 2013.

[31] Hao Zhong, Tao Xie, Lu Zhang, Jian Pei, and Hong Mei. Mapo: Mining and recommending api usage patterns. In European Conference on Object-Oriented Programming, pages 318–343. Springer, 2009.

[32] Collin McMillan, Mark Grechankin, and Denys Poshyvanyk. Detecting similar software applications. In Proceedings of the 34th International Conference on Software Engineering, pages 364–374. IEEE Press, 2012.

[33] Ali Ouni, Raula Gaikovina Kula, Marouane Kessentini, Takashi Ishio, Daniel M German, and Katsuro Inoue. Search-based software library recommendation using multi-objective optimization. Information and Software Technology, 63:55–75, 2017.

[34] Gokalsree Deb, Chaitram Pratap, Sameer Agarwal, and TAMT Meyarivan. A fast and elitist multiobjective genetic algorithm: Nsga-ii. IEEE transactions on evolutionary computation, 6(2):182–197, 2002.

[35] Sunghun Kim, Ki Pan, and E James Whitehead. When functions change their names: Automatic detection of origin relationships. In In Reverse Engineering, 12th Working Conference on, pages 10–pp. IEEE, 2005.

[36] Zhenchang Xing and Eleni Stroulia. Api-evolution support with diff-catchup. IEEE Transactions on Software Engineering, 35(12):818–836, 2007.

[37] Hoan Anh Nguyen, Tung Thanh Nguyen, Gary Wilson Jr, Anh Tuan Nguyen, Miryung Kim, and Tien N Nguyen. A graph-based approach to api usage adaptation. In ACM Sigmetrics, volume 45, pages 302–321. ACM, 2010.

[38] Wei Wu, Yann-Gaël Guéhéneuc, Giuliano Antoniol, and Miryung Kim. Aura: a hybrid approach to identify framework evolution. In Software Engineering, 2010 ACM/IEEE 32nd International Conference on, volume 1, pages 325–334. IEEE, 2010.

[39] Rahul Pandita, Raoul Praful Jetley, Sithu D Sudarsan, and Laurie Williams. Discovering likely mappings between apis using text mining. In Source Code Analysis and Manipulation (SCAM), 2015 IEEE 15th International Working Conference on, pages 231–240. IEEE, 2015.

[40] Rahul Pandita, Raoul Jetley, Sithu Sudarsan, Timothy Menzies, and Laurie Williams. Tmap: Discovering relevant api methods through text mining of api documentation. Journal of Software: Evolution and Process, 29(12), 2017.
[41] Amruta Gokhale, Vinod Ganapathy, and Yogesh Padmanaban. Inferring likely mappings between APIs. In Proceedings of the 2013 International Conference on Software Engineering, pages 82–91. IEEE Press, 2013.

[42] Sarah Fakhoury, Devjeet Roy, Sk Adnan Hassan, and Venera Arnaoudova. Improving source code readability: theory and practice. In Proceedings of the 27th International Conference on Program Comprehension, pages 2–12. IEEE Press, 2019.

[43] Anas Shatnawi, Abdelhak-Djamel Seriai, Houari Sahraoui, and Zakarea Alshara. Reverse engineering reusable software components from object-oriented APIs. Journal of Systems and Software, 131:442–460, 2017.

[44] Simone Scalabrino, Mario Linares-Vásquez, Denys Poshyvanyk, and Rocco Oliveto. Improving code readability models with textual features. In 2016 IEEE 24th International Conference on Program Comprehension (ICPC), pages 1–10. IEEE, 2016.

[45] Danilo Silva, Nikolaos Tsantalis, and Marco Tulio Valente. Why do we refactor? confessions of github contributors. In Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering, pages 858–870. ACM, 2016.

[46] Liang Tan and Christoph Bockisch. A survey of refactoring detection tools. In Software Engineering (Workshops), pages 100–105, 2019.

[47] Joshua D Angrist and Jörg-Steffen Pischke. Mostly harmless econometrics: An empiricist’s companion. Princeton University Press, 2008.

[48] Diego Cedrim, Leonardo Sousa, Alessandro Garcia, and Rohit Gheyi. Does refactoring improve software structural quality? a longitudinal study of 25 projects. In Proceedings of the 30th Brazilian Symposium on Software Engineering, pages 73–82. ACM, 2016.