**Influence of Technical and Social Factors for Introducing Bugs**

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**ABSTRACT**

As the modern open-source paradigm makes it easier to contribute to software projects, the number of developers involved in these projects keep increasing. This growth in the amount of developers makes it more difficult to deal with harmful contributions. Recent researches have found that technical and social factors can predict the success of contributions to open-source projects on GitHub. However, these researches do not study the relation between these factors with the introduction of bugs. Our study aims at investigating the influence of technical (such as, developers’ experience) and social (such as, number of followers) factors on the introduction of bugs, using information from 14 projects hosted on GitHub. Understanding the influence of these factors may be useful to developers, code reviewers and researchers. For instance, code reviewers may want to double check commits from developers that present bug-related factors. We found that technical factors have a consistent influence in the introduction of bugs. On the other hand, social factors present signs of influence in bug introduction that would require more data to be properly evaluated. Moreover, we found that perils present in the mining of GitHub may impact the factors results.

**CCS CONCEPTS**

- General and reference → Metrics;  
- Software and its engineering → Software configuration management and version control systems;  
- Software libraries and repositories;

**KEYWORDS**

GitHub Mining, Bugs, Version Control System

1 INTRODUCTION

The modern open-source development paradigm [11] makes it easier to contribute to open-source projects. However, it also makes the process of evaluating contributions a hard task for project managers [6]. Such paradigm allows several developers with different levels of experience to work simultaneously on the same projects. Inevitably, during the development process of a software, developers make changes that introduce problems [15]. Collaborative coding environments like *GitHub* provide a rich source of information on technical (such as developers’ experience) and social (such as interactions among developers) factors related to developers and their contributions.

Previous studies [5, 6, 18] indicates that both technical and social factors impact the acceptance rate of contributions on GitHub. Also, prior work [3, 7, 8, 12, 14] studied the categorization of commits, either by size or nature, with the intention of define developer’s behavior. However, those researches focus only on how developers code is pushed to the repositories given technical and social factors. In this context, we still lack research on the relation between these factors with the introduction of bugs.

Understanding the influence of those factors in the introduction of bugs may be useful for developers, reviewers and software engineering researchers. For example, in case a developer with bug-related factors and low expertise in a project decides to perform a pull request, code reviewers might spend a little more time to better analyze the request, avoiding potential bugs.

To perform our study, we collected data from 14 open-source projects hosted on GitHub. In particular, we collected 7,711 bug reports and computed 12 metrics. We use these metrics to measure the technical and social factors we focus on this study. To evaluate the correlation between technical and social factors and the introduction of bugs, we use the Spearman rank correlation coefficient [13]. We evaluate factors like developers’ experience, habit to follow technical contribution norms, interactions with the community of a project, and general community status. Our results suggest that the developers’ experience, habit to follow technical contribution norms, and interactions with the community have a consistent influence in the bugs introduction. Also, even though the community status of developers present a moderate influence in the bugs introduction, we need further analyses to properly evaluate the statistical significance of these signs.

During our mining activities, we also analyze the impact of perils. In this context, a previous study [9] presented ten perils that affect GitHub data regarding the activities. Here, we identified that two out of the ten perils may impact our results. Hence, we used the Wilcoxon Rank Sum Test [20] to evaluate the statistical significance of this impact. The results suggest that one of these perils has a significant impact on the metrics we used to measure the technical factors analyzed in our study.

In summary, this paper provides the following contributions:

1https://github.com/
2 STUDY DESIGN

Open-source environments, such as GitHub, made it easier that developers with different technical capabilities and social interactions contribute actively and simultaneously on the same software project. In such environments, these developers can perform a variety of activities, like, add commits, open/close pull requests and issues, discuss on contributions. Even though developers can collaborate in different projects, their technical capabilities and social interactions can be determining factors to the quality of a software. For example, a novice developer can introduce bugs when performing some commits. Previous studies [5, 6, 18] have not measured the influence of these factors on the bugs introduction. In this context, our study aims at answering the RQ1 research question, which investigates the influence of different factors on the introduction of bugs in open-source software projects.

RQ1: Which factors influence the introduction of bugs?

To answer RQ1, we analyze four research hypotheses that investigates the influence of factors related to the developers’ experience (H1), technical contribution norms (H2), interactions in communities of projects (H3) and status in the general community (H4) on the introduction of bugs.

H1. The more experienced the developers are, the less likely that their commits introduce bugs.

A previous study [4] shows that experienced developers may introduce less bugs since they have a clearer understanding of the source code. However, the authors evaluate the developer’s experience by considering only the number of days that he is associated to a project. Only this metric (number of days) is not capable to characterize this factor. For example, the developers’ experience may increase as they perform more commits or open/close pull requests in a project. Hence, we intend to evaluate the H1 hypothesis in order to analyze other metrics, which can provide a more comprehensive analysis regarding the relation between developers’ experience and bug introduction.

H2. The more technical contribution norms the developers follow, the less likely that their commits introduce bugs.

According to [2], project managers prefer to receive contributions that follows certain norms, such as, test inclusion, size and legibility, aiming to improve the software quality. In addition, a previous study [15] shows that buggy commits are roughly three times larger than commits that are not related to bugs. Such findings indicate that may exist a relation between technical contribution norms and the introduction of bugs. Hence, we decide to analyze the H2 hypothesis, which aims to investigate the influence of such norms on bugs introduction.

H3. The higher the status of developers in general community, the less likely that their commits introduce bugs.

A previous study [18] shows that GitHub contributions from developers at a higher community status are more likely to be accepted. We hypothesize that these developers are also more experienced. As a consequence, their commits would be less likely to introduce bugs. In this context, we investigate the H3 hypothesis, which aims to evaluate the relation between developers with a higher general community status and bugs introduction.

H4. The more the developers interact with the community of a project, the less likely that their commits introduce bugs.

According to [18], contributions to open-source projects with long discussions (or high number of comments) are less likely to be accepted. We hypothesize that developers who discuss more about contributions also learn more about the projects, even if their contributions have not been accepted. As a consequence, developers may become more experienced and their commits would be less likely to introduce bugs. To evaluate this hypothesis, we defined the H4 that aims to investigate the influence on the bug introduction of interactions with the community of a project hosted on GitHub.

RQ2: How relevant is the impact of GitHub Mining Perils?

According to [9], while GitHub is a rich source of data on software development, mining GitHub data for research comes with various potential perils. Several works [1, 6, 19, 23] only discuss GitHub Mining Perils as threats to their validity [19, 23] or simply apply avoidance strategies [1, 6]. However, none of these works analyze the impact of avoiding these perils. Hence, we implemented existing avoidance strategies and then evaluated the impact of two well-known GitHub Mining Perils [9], which may impact our results. In the next sections, we provide a detailed description of the methodology used to answer our research questions.

2.1 Project Selection

To perform our study, we manually selected 14 GitHub Java projects according to the following criteria:

- The project should be open-source and contains its change history hosted on GitHub;
- The project should use the GitHub issues as a bug-tracking tool;
- The project should be currently active and has been maintained or evolved for a long period of time;

Table 1 summarizes these projects according to their characteristics. Note that each project has a high number of developers involved, varying from 68 (HikariCP) up to 902 (Elasticsearch). Moreover, the projects have a large amount of commits and bugs associated to them. All this data enable us to perform a deep analysis regarding the relation between factors associated to developers and bugs introduction.
2.2 Collecting Bug Reports

The GitHub issues are useful to keep track of tasks, enhancements and bugs related to a project. Furthermore, developers can associate labels to each issue in order to characterize it. For example, an issue can be opened to fix a bug and a “bug” label can be associated to this issue. After fixing the bug, the issue can be closed by a project manager.

To collect the reports of fixed bugs in the selected projects, we mined the closed issues related to bugs (or defects) existing in each project. In order to identify these issues, we verified the ones containing the “bug” or ‘defect’ labels. As a result of this process, we collected 7,711 bug reports from the 14 projects analyzed.

2.3 Locating Bug-introducing Changes

During the development of a software system, developers make changes in the source code, either to add new functionality, repair an existing bug or restructure the code. Inevitably, some of these changes can introduce bugs. We will further refer to these changes as bug-introducing changes [10].

To locate bug-introducing changes in the selected projects, we implemented the SZZ algorithm [15]. It aims at identifying the commits that introduced a bug in a software. In order to locate the commits that introduced bugs, the SZZ algorithm requires the commits that fixed these bugs.

GitHub provides a functionality to close an issue using commit messages. For example, prefacing a commit message with the keywords "Fixes", "Fixed", "Fix", "Closes", "Closed", or "Close", followed by an issue number, such as, "Fixes #12345", will automatically close the issue when the commit is merged into the master branch. This way, when this strategy is used to close a bug issue, we assume the commit that closed the issue as being the bug’s fix commit. On the other hand, if this strategy is not used to close a bug issue, we employ a heuristic that assumes the last commit immediately before the date of the issue closing as being the bug’s fix commit.

We employed the SZZ algorithm for each collected bug from the 14 selected projects. As a result, we obtained a total of 12,006 bug-introducing changes.

2.4 Data Collection

To collect the data that will be further used to compute the metrics related to technical and social factors, we use the GitHub API to:

1. Collect the identifier on GitHub of the developers that introduced at least one bug;
2. Extract the commits, issues and pull requests performed by these developers;
3. Mine the public profiles of these developers.

As a result of this process, we obtained information about 528 developers, which introduced at least one bug. Moreover, we collected 96,277 commits, 34,687 pull requests and 64,998 issues related to the 14 projects analyzed.

2.5 Metrics

After creating our dataset, we use it to compute 14 metrics grouped according to four factors, as follows:

Developers’ Experience: We use five metrics to characterize the developers’ experience. We compute the values of these metrics since the first contribution of a developer to the project and until the moment that a bug-introducing change occurs. These metrics are detailed below:

- **Number of Commits (NC):** this metric represents the number of commits authored by a developer;
- **Number of Active Days in Project (NADP):** this metric indicates how many days a developer has been active, i.e., committing;
- **Number of Days in Project (NDP):** this metric counts the number of days that a developer has been associated to a project, independently if he is contributing or not;
- **Number of issues Activities (NIA):** this metric measures the number of issues opened or closed by a developer;
- **Number of Pull Requests Activities (NPRA):** this metric measures the number of pull requests opened or closed by a developer;

Even though such metrics may be not sufficient to fully characterize experience, they represent different aspects of the activities performed by developers when they contribute to a GitHub project.

Technical Contribution Norms: We use three metrics to characterize the factor related to the technical contribution norms. The process of computing these metrics is the same adopted when we computed the developer’s experience metrics. These three metrics are detailed below:

- **Number of Tests Included (TI):** this metric measures the quantity of commits that contain tests. To extract it, we adopted the procedure defined by [18]. First, we retrieve all the files modified in a commit authored by a developer. Then, we check how many files contain the “test” word in its path-name;
- **Median of Modified Files (MMF):** this metric measures the median of modified files among all the commits authored by a developer;
- **Median of Lines Changed (MLC):** this metric represents the median of changed lines among all the commits authored by a developer. A changed line can be an addition or a deletion in a commit;

| Table 1: Selected GitHub Projects |
|----------------------------------|
| Project             | Domain       | Commits | Bugs | Developers |
|----------------------|--------------|---------|------|------------|
| Elasticsearch        | Search Engine| 28,653  | 2,305| 902        |
| Spring-boot          | App Builder  | 13,134  | 949  | 395        |
| Netty                | Framework    | 5,800   | 1,136| 295        |
| Bazel                | Build System | 12,082  | 854  | 261        |
| Presto               | Query Engine | 11,413  | 296  | 198        |
| RxJava               | Library      | 5,161   | 208  | 179        |
| Signal-Android       | Messenger    | 3,203   | 509  | 159        |
| OkHttp               | HTTP Client  | 3,060   | 282  | 144        |
| Guava                | Library      | 4,420   | 293  | 129        |
| Hystrix              | Library      | 2,083   | 73   | 104        |
| Fresco               | Library      | 1,499   | 169  | 104        |
| ExoPlayer            | Media Player | 3,228   | 334  | 85         |
| Es-hadoop            | Plugin       | 1,728   | 201  | 71         |
| HikariCP             | Library      | 2,488   | 102  | 68         |
We were able to identify two GitHub Mining Perils reported in [9] as developers that introduced bugs. We will further refer to this peril as Peril I.

The second identified peril states that the majority of the merged pull requests are not merged through GitHub facilities and, then, are not tracked as "merged". This peril is a consequence of the avoidance strategy applied to tackle the first peril, since we also consider the activity in the pull requests that were merged. The recommended avoidance strategy is to use any of the four heuristics defined in [5] to identify pull requests that were merged outside GitHub. We implemented the first (Heuristic I) and second (Heuristic II) heuristics, resulting in a total of 101 pull requests related to developers that introduced bugs. We will further refer to this peril as Peril II.

2.7 Data Analysis
To answer RQ1, we analyze the H1-H4 hypotheses in terms of the factors related to them. For each factor, we use the Spearman (ρ) rank correlation to evaluate the correlation coefficient between the metrics, used to measure the factor, and the percentage of buggy commits performed by the developers. We choose the Spearman rank correlation because it is more adequate to evaluate relationships between variables when at least one of them is skewed or contain outliers [13], which is the case for the majority of our metrics. After generating the correlation coefficients, we use the classification defined in [13] to determine their strength. Such classification defines five categories, as described in Table 2. These categories allow us to evaluate and compare the strength of the correlations between metrics and the bugs introduction.

Table 2: Categorization of Correlation Coefficients [13]

| Correlation Coefficient | Categorization |
|-------------------------|---------------|
| .90 ≤ |ρ| ≤ 1.00        | Very high    |
| .70 ≤ |ρ| < .90         | High         |
| .50 ≤ |ρ| < .70         | Moderate      |
| .30 ≤ |ρ| < .50         | Low          |
| .00 ≤ |ρ| < .30         | Negligible   |

To verify if exists a statistically significant difference between the values of the metrics when the perils were avoided and when they were not. We choose this test because we can decide whether two populations are identical or not without assuming that the metrics follow a normal distribution, which is the case for the majority of them. We employ the .05 significance level for this test.

3 RESULTS AND DISCUSSION
In this section, we present and discuss our main results. The presentation of the results and the discussions are organized in terms of the two research questions described in Section 2.

3.1 RQ1: Which factors influence the introduction of bugs?
To answer RQ1, we hypothesize factors that may influence the introduction of bugs, as described in Section 2. H1 hypothesize on the experience of developers; H2 hypothesize on the habit of following technical contribution norms; H3 hypothesize on the general community status of developers; and H4 hypothesize on the interactions of developers with the communities of projects on GitHub. We now present the hypotheses results and examine their validity.

H1. The more experienced the developers are, the less likely that their commits introduce bugs.

Table 3 presents the results that support the discussions about H1. We describe the correlation coefficients and its statistical significance (we consider a p-value < 0.05) by applying the Spearman correlation test for each metric and analyzed project. The first column presents the name of the analyzed projects and the remaining...
columns describe the correlation coefficients of the Number of Commits (NC), Number of Active Days in Project (NADP), Number of Days in Project (NDP), Number of Issues Activities (NIA) and Number of Pull Requests Activities (NPRA), respectively. We use the ✓ symbol to indicate if the correlation coefficient is statistically significant, and the ✗ symbol otherwise.

Table 3: Correlations between Developer Experience and Percentage of Buggy Commits

| Project       | NC  | NADP | NDP  | NIA  | NPRA |
|---------------|-----|------|------|------|------|
| Elasticsearch | -0.3 ✓ | -0.3 ✓ | -0.3 ✓ | -0.1 ✓ | -0.5 ✓ |
| Spring-boot  | -0.3 ✓ | -0.3 ✓ | -0.5 ✓ | -0.5 ✓ | 0 ✓ |
| Netty        | -0.4 ✓ | -0.1 ✓ | -0.1 ✓ | 0.3 ✓ | 0.5 ✓ |
| Bazel        | -0.5 ✗ | -0.5 ✓ | -0.3 ✓ | -0.2 ✗ | -0.1 ✓ |
| Presto       | -0.6 ✗ | -0.6 ✓ | -0.3 ✓ | -0.1 ✓ | -0.6 ✓ |
| RxJava       | 0.1 ✓ | 0.5 ✓ | 0.7 ✓ | 0.3 ✓ | 0.6 ✓ |
| Signal-Android | -0.9 ✓ | -0.9 ✓ | -0.8 ✓ | -0.8 ✓ | -0.7 ✓ |
| OkHttp       | -0.3 ✓ | -0.4 ✓ | -0.6 ✓ | -0.2 ✗ | -0.2 ✓ |
| Guava        | -0.5 ✓ | -0.3 ✓ | -0.1 ✓ | 0.4 ✓ | - |
| Hystrix      | -0.8 ✓ | -0.8 ✓ | -0.7 ✓ | 0.1 ✓ | 0.1 ✓ |
| Fresco       | -0.8 ✗ | -0.7 ✓ | -0.6 ✓ | -0.6 ✗ | -0.6 ✓ |
| ExoPlayer    | -0.4 ✗ | -0.5 ✓ | -0.5 ✓ | -0.3 ✓ | -0.3 ✓ |
| Es-hadoop    | 0.1 ✓ | 0.1 ✓ | 0.2 ✓ | 0.1 ✓ | -0.2 ✓ |
| HikariCP     | 0.4 ✓ | 0.4 ✓ | 0.5 ✓ | 0.6 ✓ | 0.6 ✓ |

NC. Regarding the NC metric, we observe a very high (see classification described in Section 2.7) negative correlation between this metric and the percentage of buggy commits in Signal-Android. Such result indicates a decrease in the percentage of introduced bugs as we have an increase in the number of commits in the Signal-Android project, as shown in Figure 1.

![Figure 1: Percentage of Buggy Commits vs NC – Signal-Android](image1)

The Hystrix and Fresco projects present a correlation coefficient (equal to −0.8) slightly lower than Signal-Android, reaching a high negative correlation. Three projects present moderate negative correlations varying from −0.5 to −0.6. Note that only HikariCP presents a positive correlation that is statistically significant and not negligible. We also note that all the projects that obtained negative correlation coefficients presented statistically significant results. Therefore, in the majority of the projects analyzed, we observe a decrease in the percentage of introduced bugs as we have an increase in the number of commits.

NADP. Similarly to the NC metric, only three projects obtained positive correlation coefficients when we consider the NADP metric. However, only the RxJava project was able to reach a moderate correlation. On the other hand, six out of 11 projects that obtained negative coefficients present a correlation higher or equal to moderate, reaching a very high correlation in Signal-Android. This very high correlation indicates a decrease in the percentage of introduced bugs as we have an increase in the number of active days in the Signal-Android project, as illustrated in Figure 2.

![Figure 2: Percentage of Buggy Commits vs NADP – Signal-Android](image2)

![Figure 3: Percentage of Buggy Commits vs Days Active in Project – Signal-Android](image3)

While Fresco and Hystrix present high correlation coefficients, three projects present moderate negative correlations. In addition, three projects present a low correlation equal to −0.3. Only one project presented a negligible negative correlation. Just as NC, we obtained statistically significant results in all projects that present negative correlation coefficients when we analyze the NADP metric. Such results indicate a decrease in the percentage of introduced bugs as the developers dedicate more days working actively in the majority of the projects analyzed.

NDP. Similarly to the NC and NADP metrics, only three projects presented positive correlations for the NDP metric. On the other hand, six out of nine projects that presented negative correlation coefficients present a correlation higher or equal to moderate, reaching a high correlation in the Signal-Android and Hystrix projects. These high negative correlations indicate a decrease in the percentage of introduced bugs as we have an increase in the number of days in Signal-Android and Hystrix. We observe this tendency in Figure 3, which represent the relation between the number of days (X-axis) and the percentage of introduced bugs (Y-axis) in the Signal-Android project.

Four projects present moderate negative correlations varying from −0.5 to −0.6. Moreover, three projects presented low negative correlations equal to −0.3. Only two projects present negligible negative correlations. Also, note that the vast majority of the projects...
This high correlation indicates a decrease in the percentage of introduced bugs as we have an increase in the number of days in which the developers are associated with the project.

**NIA.** Regarding the NIA metric, we note a high negative correlation in *Signal-Android* by reaching a coefficient equal to -0.8. This high correlation indicates a decrease in the percentage of introduced bugs as we have an increase in the number of issues activities in the *Signal-Android* project, as depicted in Figure 4.

![Figure 3: Percentage of Buggy Commits vs NDP – Signal-Android](image)

We observe that two projects present moderate negative correlations. Also, five more projects present negative correlations. However, they were not able to obtain a correlation higher than low. The remaining six projects obtained a positive correlation. However, only *HikariCP* was able to obtain a moderate one. In a nutshell, we observe a greater number of projects with negative correlations. Note also that the negative correlations were able to reach higher coefficients than the positive ones. Moreover, all the negative correlations present coefficients statistically significant. Such results indicate a decrease in the percentage of introduced bugs as the developers perform more activities related to GitHub issues, i.e., opening or closing issues, in the majority of the projects analyzed.

**NPRA.** Similarly to the NIA metric, only five projects obtained positive correlations for the NPRA metric. While three projects present moderate correlations, *Hystrix* and *Spring-boot* obtain negligible ones. The remaining projects present negative correlations, reaching a high correlation equal to -0.7 in *Signal-Android*. Also, three other projects present moderate correlations. Just as the metrics (NC, NADP and NIA) previously discussed, we obtain coefficients statistically significant for all the negative correlations observed in the NPRA metric. Therefore, in the majority of the analyzed projects, we observe a decrease in the percentage of introduced bugs as the developers perform more activities related to GitHub pull requests.

In our study, we characterize the developers’ experience in terms of the NC, NDP, NIA and NPRA metrics. For the majority of the projects analyzed, we observe a decrease of the number of introduced bugs as we have an increase in such metrics. Such results suggest that the more experienced developers are in a project, the less likely that their commits introduce bugs.

**H2.** The more technical contribution norms the developers follow, the less likely that their commits introduce bugs.

Table 4 presents the results that support the discussions about **H2.** The first column presents the name of the analyzed projects and the remaining columns describe the Spearman rho rank correlation coefficients of the Median of Modified Files (MMF), Median of Lines Changes (MLC) and Number of Tests Included (NTI), respectively. We use the ✓ symbol to indicate if the correlation coefficient is statistically significant by considering a p-value < 0.05, and the ✗ symbol otherwise.

| Project       | NTI | MMF | MLC |
|---------------|-----|-----|-----|
| Elasticsearch  | -0.4(✓) | 0.2(✓) | 0.3(✓) |
| Spring-boot   | -0.2(✓) | 0.6(✓) | 0.7(✓) |
| Netty         | -0.2(✓) | 0.6(✓) | 0.8(✓) |
| Bazel         | -0.4(✓) | 0.3(✓) | 0.4(✓) |
| Presto        | -0.6(✓) | -0.1(✗) | 0.2(✓) |
| RxJava        | 0.4(✓) | 0.7(✓) | 0.8(✓) |
| Signal-Android| -0.6(✓) | 0.5(✓) | 0.6(✓) |
| OkHttp        | -0.1(✓) | 0.6(✓) | 0.7(✓) |
| Guava         | -0.5(✓) | 0.4(✓) | 0.5(✓) |
| Hystrix       | 0.1(✗) | 0.4(✗) | 0.8(✗) |
| Fresco        | -0.6(✗) | 0.7(✓) | 0.7(✓) |
| ExoPlayer     | -0.5(✗) | 0.1(✗) | 0.5(✓) |
| Es-hadoop     | 0.1(✗) | 0.2(✗) | 0.4(✓) |
| HikariCP      | 0.5(✗) | 0.2(✗) | 0.4(✓) |

**NTI.** In the case of the NTI metric, we could not obtain a high correlation with the percentage of buggy commits in none of the analyzed projects. However, three projects present moderate negative correlations, which indicate a decrease in the percentage of introduced bugs as we have an increase in the number of tests.
included in the commits of these projects. For example, Figure 5 represents this tendency in the Signal-Android project.

Figure 5: Percentage of Buggy Commits vs NTI – Signal-Android

While Elasticsearch and Bazel present low negative correlations of −0.4, Spring-boot, Netty and OkHttp present negligible negative correlations. Only RxJava and HikariCP present low and moderate positive correlations, respectively. Such results indicate a decrease in the percentage of introduced bugs as the developers add more tests to their commits in the majority of the projects analyzed.

MMF. Differently from the previous analysis in which a greater number of projects presented negative correlations, the vast majority of the projects present positive correlations between the number of buggy commits and the median of modified files (MMF). Four projects present moderate positive correlations ranging between 0.5 and 0.6. Moreover, three other projects present low positive correlations. We observe that only the Presto, which reach a negative correlation, and Hystrix projects do not present statistically significant coefficients. Therefore, in the majority of the analyzed projects, we note an increase in the percentage of introduced bugs as the developers perform commits with a greater number of modified files.

MLC. Regarding the MLC metric, all projects present positive coefficients, reaching high correlations in six projects. Three projects present moderate correlations. Only the Presto project presents a negligible correlation. Also, note that only Hystrix does not present correlation coefficients statistically significant. Such results indicate an increase in the percentage of introduced bugs as the developers perform commits with a higher number of lines changed.

We characterize the technical contribution norms in terms of the NTI, MMF and MLC metrics. We observed a decrease of the number of introduced bugs as we have an increase in the NTI metric and a decrease in the MMF and MLC metrics. Such results suggest that the more technical contribution norms developers follow, the less likely that their commits introduce bugs.

H3. The higher the status of developers in general community, the less likely that their commits introduce bugs.

Table 5 presents the results for H3. The first column presents the name of the analyzed projects and the remaining columns describe the correlation coefficients of the Number of Followers (NF), Number of Public Repositories (NPR) and Number of Public Gists (NPG), respectively. Again, we use the ✓ symbol to indicate if the correlation coefficient is statistically significant, and the ✗ symbol otherwise.

Table 5: Correlations between General Community Status and Percentage of Buggy Commits

| Project     | NF    | NPG   | NPR   |
|-------------|-------|-------|-------|
| Elasticsearch| -0.3  | 0     | 0     |
| Spring-boot | -0.4  | -0.3  | -0.4  |
| Netty       | -0.1  | -0.2  | -0.2  |
| Bazel       | 0     | -0.2  | 0     |
| Presto      | -0.3  | -0.2  | -0.2  |
| RxJava      | 0     | 0.4   | 0.4   |
| Signal-Android| -0.3  | -0.1  | 0     |
| OkHttp      | -0.4  | -0.2  | 0     |
| Guava       | -0.8  | -0.7  | -0.4  |
| Hystrix     | -0.4  | -0.5  | 0.1   |
| Fresco      | 0     | 0.8   | 0.4   |
| ExoPlayer   | 0     | -0.1  | 0.4   |
| Es-hadoop   | -0.8  | -0.8  | -0.1  |
| HikariCP    | -0.1  | -0.4  | -0.4  |

NF. Regarding the number of followers (NF), two projects (Guava and Es-hadoop) present high negative correlations equals to −0.8, which suggest a decrease in the percentage of introduced bugs as we have an increase in the number of followers that developers have on GitHub. Elasticsearch and Spring-boot presented low negative correlations of −0.3 and −0.4, respectively. Note that we could obtain coefficients statistically significant only for these four projects. The remaining projects present low or negligible negative correlations without statistical significance. Even though we could obtain statistically significant coefficients only to four projects, the vast majority of the projects present negative correlation coefficients. Therefore, we observe signs that the percentage of introduced bugs may decrease as the developers have more followers on GitHub. However, further studies are still needed for this claim.

NPG. Similarly to the NF metric, Guava and Es-hadoop present high negative correlations in the NPG metric. Such result suggests a decrease in the percentage of introduced bugs as we have an increase in the number of public Gists that developers have hosted on GitHub. On the other hand, we observe a high positive correlation in Fresco, which could indicate a contradictory conclusion. However, besides this project, only two more projects present positive correlations. Therefore, we observe more signs that the percentage of introduced bugs may decrease as the developers have more Gists hosted on GitHub. Like the NF metric, we could not obtain statistically significant coefficients for the vast majority of the analyzed projects.

NPR. Differently from the previous analysis, none of the analyzed projects present a correlation higher than low. Indeed, we obtained negligible correlations in nine out of the 14 projects analyzed. The remaining projects present low correlations.
we could not observe evidence about a correlation between the number of buggy commits and the NPR metric.

In our study, we characterize the general community status of a developer in terms of the NF, NPG and NPR metrics. We observed signs of a decrease of the number of introduced bugs as we have an increase in the NF and NPG metrics. Even though the NPR metric does not contribute to the hypothesis validation, such results suggest that the more prolific developers are on GitHub, the less likely that their commits introduce bugs.

**H4. The more the developers interact with the community of a project, the less likely that their commits introduce bugs.**

Table 6 presents the results for H4. The first column presents the name of the analyzed projects and the remaining columns describe the correlation coefficients of the Number of issues Activities (NIA), Number of Pull requests Activities (NPRA) and Number of Comments (NCO), respectively.

**Table 6: Correlations between Developer Interaction with a Project’s Community and Percentage of Buggy Commits**

| Project      | NCO  |
|--------------|------|
| Elasticsearch | -0.2 (√) |  
| Spring-boot  | -0.5 (√) |  
| Netty        | 0.5 (√) |  
| Bazel        | -0.1 (√) |  
| Presto       | -0.4 (√) |  
| RxJava       | 0.6 (√) |  
| Signal-Android | -0.8 (√) |  
| OkHttp       | -0.3 (√) |  
| Guava        | 0.5 (√) |  
| Hystrix      | -0.7 (√) |  
| Fresco       | -0.6 (√) |  
| ExoPlayer    | -0.4 (√) |  
| Es-hadoop    | 0.1 (✗) |  
| HikariCP     | 0.5 (✓) |  

**NCO.** Regarding the number of comments (NCO) metric, we observe two high negative correlations with the percentage of buggy commits in the Signal-Android and Hystrix projects. These high correlations indicate a decrease in the percentage of introduced bugs as we have an increase in the number of comments. Figure 6 presents the relation between buggy commits and NCO in the Signal-Android project.

We observe that two projects presented moderate negative correlations, while three projects presented low ones. Moreover, all projects that obtained negative correlation coefficients present statistically significant. Therefore, results indicate a decrease in the percentage of introduced bugs as the developers discuss more in the majority of the projects analyzed.

The results of the four hypothesis indicate that the developers’ experience, the habit of following contribution norms and the interaction with the community of projects on GitHub have a consistent influence in the introduction of bugs. Regarding the general community status of developers, we were able to find signs of influence in the introduction of bugs. However, further studies are still needed for this claim. Our findings might be useful to developers and code reviewers, since they may want to carefully verify commits from developers who present bug-related factors.

### 3.2 RQ2: How relevant is the impact of GitHub Mining Perils?

Tables 7 and 8 present the results regarding RQ2. We use the Wilcoxon Rank Sum Test to compare the values of the metrics when avoiding and when not avoiding the identified perils. While Table 7 presents the p-values of the tests for Peril I, Table 8 presents the p-values for Peril II. The first column of the tables presents the names of the analyzed projects and the remaining columns describe the statistical significance of the tests for the Number of Commits (NC), Number of Active Days in Project (NADP), Number of Days in Project (NDP), Median of Modified Files (MMF), Median of Lines Changes (MLC) and Number of Tests Included (NTI) metrics, respectively.

**Figure 6: Percentage of Buggy Commits vs NCO – Signal-Android**

**Table 7: Statistical Significance (p-value) of the Wilcoxon Rank Sum Test for Peril I**

| Project   | NC  | NADP | NDP  | MMF | MLC  | NTI  |
|-----------|-----|------|------|-----|------|------|
| Elasticsearch | 0   | 0    | 0.97 | 0   | 0    | 0    |
| Spring-boot   | 0.99 | 0.99 | 0.98 | 1   | 0.96 | 0.99 |
| Netty       | 0.17 | 0.1  | 0.76 | 0.57| 0.89 | 0.24 |
| Bazel       | 0.96 | 0.98 | 0.07 | 0.94| 0.69 | 1    |
| Presto      | 0   | 0    | 0.26 | 0   | 0    | 0    |
| RxJava      | 0   | 0    | 0    | 0.42| 0.71 | 0    |
| Signal-Android | 0.39 | 0.34 | 0.92 | 0.01| 0.25 | 0.81 |
| OkHttp      | 0   | 0    | 0    | 0.2 | 0    | 0    |
| Guava       | 1   | 1    | 1    | 1   | 1    | 1    |
| Hystrix     | 0   | 0.03 | 1    | 1   | 0    | 0.14 |
| Fresco      | 0.84 | 0.9  | 1    | 0.95| 0.62 | 1    |
| ExoPlayer   | 0   | 0    | 0    | 0   | 0    | 0    |
| Es-hadoop  | 0.99 | 0.99 | 0.99 | 0.98| 0.99 | 1    |
| HikariCP   | 0.8  | 0.68 | 0.94 | 0.25| 0.03 | 0.88 |
Peril I. We observe that the ExoPlayer project presents \( p \)-values equal to 0 for all the metrics analyzed. Elasticsearch, Presto and OkHttp present \( p \)-values slightly similar by reaching values equal to 0 in almost all the metrics, except the NDP metric. RxJava presents \( p \)-values equal to 0 in four out of six metrics. Hystrix presents only two significant \( p \)-values. Signal-Android and HikariCP present only one significant \( p \)-value in the MMF and MLC metrics, respectively. The 6 remaining projects do not present significant \( p \)-values. Note that in eight of the 14 analyzed projects we have at least one significant \( p \)-value. Therefore, such results suggest that the *employment of the avoidance strategy for Peril I (described in Section 2.6)* may significantly affect the metrics values.

### Table 8: Statistical Significance (\( p \)-value) of the Wilcoxon Rank Sum Test for Peril II

| Project         | NC  | NADP | NDP  | MMF | MLC | NTI |
|-----------------|-----|------|------|-----|-----|-----|
| Elasticsearch    | 0.09| 0.08 | 0.65 | 0.13| 0.06| 0.02|
| Spring-boot     | 0.53| 0.68 | 0.94 | 0.99| 0.67| 0.58|
| Netty           | 0.36| 0.01 | 0.71 | 0   | 0.03| 0.06|
| Bazel           | 0.78| 0.09 | 0.31 | 0.04| 0.6 | 0.75|
| Presto          | 0.86| 0.18 | 1    | 0.01| 0   | 0.33|
| RxJava          | 0.95| 0.97 | 1    | 1   | 0.86| 0.92|
| Signal-Android  | 0.96| 0.91 | 1    | 0.92| 0.94| 0.83|
| OkHttp          | 1    | 1    | 1    | 1   | 1   | 1   |
| Guava           | 1    | 1    | 1    | 1   | 1   | 1   |
| Hystrix         | 1    | 1    | 1    | 1   | 1   | 1   |
| Fresco          | 1    | 1    | 1    | 1   | 1   | 1   |
| ExoPlayer       | 0.28| 0.6  | 0.7  | 0   | 0   | 0.14|
| Es-hadoop       | 1    | 1    | 1    | 1   | 1   | 1   |
| HikariCP        | 0.89| 0.93 | 0.97 | 0.79| 0.63| 0.96|

Peril II. Differently from Peril I, we observe that Peril II has a low impact on the metrics, since we obtain significant \( p \)-values only in a few cases. While Netty presents significant \( p \)-values in three metrics, the RxJava project presents only in two. Elasticsearch and ExoPlayer present significant \( p \)-values only in the NTI and MLC metrics, respectively. The ten remaining projects do not present significant \( p \)-values. Such results are due to the fact that many pull requests found by Heuristics I and II (see Section 2.6) were not related to developers that introduced bugs. Therefore, results suggest that the *employment of the avoidance strategy for Peril II (described in Section 2.6)* does not affect significantly the metrics values.

In summary, the tests results indicate that Peril I presented a significant impact on the metrics results. On the other hand, we could not find enough signs that Peril II presents a significant impact on the metrics results. Such findings can be very useful to mining software repositories and software engineering researchers, since these results motivate the employment of avoidance strategies when mining GitHub.

## 4 THREATS TO VALIDITY

This section presents the threats to validity by following the criteria defined in Wohlin et al. [22].

### Construct Validity

The set of technical and social factors analyzed in our study may not accurately represent the reasons that may lead developers to introduce bugs. This threat was mitigated by selecting factors that were previously analyzed by researches on the contributions in open-source communities [18], [5]. Another threat to validity is to correctly identify the commits that fixed bugs. GitHub provides a functionality to close issues by commits messages or pull requests comments. We mitigated this threat by identifying as the bug-fix the commits or pull requests (the last commit) that close issues labelled as "bug" or "defect" using this functionality.

### Internal Validity

We rely on the SZZ approach to locate the introduction points of the analyzed bugs. The false positives reported by SZZ may represent a threat to internal validity. To mitigate this threat, we used a combination of heuristics proposed by Kim et al. [10] and Williams and Spacco [21] that claim to reduce the number of false positives.

### External Validity

Regarding the validity of our findings, we selected only projects in which the primary language is Java. Although we have selected a large amount of projects, with different sizes and developers, and from ten different domains, our results might not hold to projects in which the primary language is not Java. This is due to the fact that those projects have different characteristics and are part of different communities.

## 5 RELATED WORK

Correlations between developer characteristics (commit frequency and experience) and commit bugginess were previously investigated by Eyolfson et al. [4]. The authors found that developers who commit to a repository on a daily basis write less buggy commits, while developers who does it as their day-job are more likely to produce bugs. Also, the authors suggest the existence of a possible correlation between more experienced developers and less buggy commits. Sliwerski et al. [15] presents an approach to automatically locate fix-inducing commits. They found that buggy commits are roughly three times larger than other commits, measuring the size of commits by the number of touched files. This finding may indicates that developers who perform larger commits may introduce more bugs.

Many studies [3, 7, 8, 12, 14] provide commit classification strategies regarding the size and the nature of these code changes. Those strategies can be used to define the commit behaviour of developers, i.e., developers who usually perform large or maintenance commits. While [7] and [12] provided a generic approach to classify commits regarding their size and nature, Dragan et al. [3] implemented a tool, StereoCommit, that characterizes source code changes according to defined method stereotypes. [8] and [14] focus on a classification of commits by their nature for specific commit size: the first tackle large commits, while the second analyzes small changes.

The pull request acceptance is also an interesting study attribute. Tsay et al. [18] shows that pull requests which includes tests cases and few lines of code are more prone to be accepted. Also, users that have high social status, measured by the number of followers or stars at their projects, have a higher pull request acceptance rate. [16] also found that experienced developers (with more than 1k followers or core project contributors) have a higher acceptance
rate. Terrel et al. [17] discovered that a gender bias exists when contributing to open-source projects on GitHub: women’s pull requests tend to be accepted more than pull requests from men, but only when they’re not identifiable as women. Our study differs from the previous literature works by expanding the empirical studies that investigate correlations between technical (such as experience) and social (such as status in an open-source community) factors and commit bugginess. In order to evaluate the influence of more developer experience and characteristics metrics, we expand the approach presented by Eylolfson et al. [4], also using some technical and social factors summarized by Soko et al. [16], such as interaction with a project’s community and the habit to follow technical contribution norms. Also, we investigate the impact to our study of different existing perils when mining GitHub [9]. Our aim is to provide a more extensive and complete study regarding the investigation of possible correlation between bug-introducing changes and the developer metrics surveyed above.

6 CONCLUSION
This paper studies the influence of different technical and social factors on the likelihood of developers to introduce bugs. We analyzed 14 open-source Java projects, accounting for a total of 7,711 bug reports and 12,006 bug-introducing changes. To understand which factors may influence the introduction of bugs by developers, we hypothesize on four different factors, namely, developer experience, habit to follow technical contribution norms, interaction with the community of projects and general community status.

We analyzed the influence of the selected factors on the introduction of bugs by applying Spearman Rank Sum correlations. Results indicate that as developers’ experience, habit of following technical contribution norms and interaction with the community of projects on GitHub increase, the likelihood of introducing bugs decreases. Therefore, results indicate that these factors have a consistent influence in the introduction of bugs. Regarding the general community status of developers, we were able to find signs of influence in the introduction of bugs. However, further studies are still needed for this claim. We believe that these findings benefit developers, project reviewers and software engineering researchers, since, for example, they may want to carefully verify contributions from inexperienced developers.

We also evaluated the impact of GitHub Mining Perils in our study. Results show that measuring the activity of a repository independently of the contributions from outsiders (Peril I) significantly affect the values of the metrics we defined, since the majority of the projects present at least one metric affected by this peril. Results also show that relying on the “merged” status of pull requests on GitHub (Peril II) did not affected significantly the values of these metrics, since only four of the 14 analyzed projects were affected by this peril.

As future work, we intend to expand this investigation to account for more projects of different programming languages and domains. We also pretend to asses the influence of contributions outside an analyzed project, to better understand developers’ experience and interactions.

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