# Does the First-Response Matter for Future Contributions? A Study of First Contributions\*

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*Abstract—Context:* Open Source Software (OSS) projects rely on a continuous stream of new contributors for sustainable livelihood. Recent studies reported that new contributors experience many barriers in their first contribution. One of the critical barriers is the social barrier. Although a number of studies investigated the social barriers to new contributors, to the best of our knowledge, the relationship between the first response to the first contributions and their future contributions has not been studied comprehensively.

*Objective:* In this registered report, we introduce the study protocols that investigate the correlation between the first response given to the first contributions and the future contribution. First, we performed a preliminary survey to manually explore the sentiments of the first response. Preliminary analysis confirms that the first responses are mainly neutral.

*Method:* Our execution plan includes both qualitative and quantitative approaches with three research questions. We inspect the first response of the first contributions, investigate the effects of characteristics of the first response to the interaction between first-time-contributor and project contributors, and find the impact of the interactions between other contributors.

#### I. INTRODUCTION

GitHub is one of the well-known repository hosting tools that are being used for Open Source Software (OSS) projects. In 2021, Github reported over 60 million repositories created in recent years and over 56 million contributors; a massive number of new contributors strive to present their skills to the world's largest OSS community through project contributions. <sup>1</sup> GitHub strives on social coding, which is the collaboration of both new contributors and the current community of contributors [1].

OSS projects truly rely on a continuous stream of new contributors [2]. A large number of recent studies have provided evidence that new contributors have encountered various barriers ranging from difficulty in finding assistance to receiving negative responses from other contributors [3]. In consequence, the new contributor turnover rate has been increased [4]. For example, [2] reported that less than 18% of new contributors keep continuing to contribute to the Hadoop Common Project. This possibly leads to the peril of OSS projects' livelihood and sustainability [5]. Zhou and Mockus

[6] revealed that the probability for a new contributor to becoming a long-term contributor is associated with his/her willingness and environment. An investigation on specific social coding tactics found that new contributors who socialized with welcome and assistance messages and constructive criticism tend to encourage future contributions[6]. Steinmacher et al. [4] mentioned that new contributors had experienced delayed responses, impolite comments, and many more issues regarding the social barriers. Furthermore, Gousios et al. [7] reported that responsiveness is the most reported challenge that new contributors experience.

Figure 1 shows a screenshot of a negative response to a new contributor on a pull request in GitHub. In terms of GitHub projects, we consider any pull request as a contribution, with the comments exchanged during the review of the pull request as the interactions between developers. Hence, the first response is the first comment to the pull request submitted by a newcomer to that repository. In this case:

"This behavior seems undesired. I'd rather we kept the current behavior than follow npms current semantics."

We hypothesize that this negative message may cause an unpleasant feeling and subsequently lead to the discontinuity of their contributions (i.e., such as further interactions within the same pull request or future contributions), especially for a novice contribution that can be easily demotivated. Although a number of studies investigated the social barriers to new contributors, to the best of our knowledge, the relationship between the first response to the first contributions and their future contributions has not been studied comprehensively.

Therefore, in this registered report, we lay a foundation for understanding the correlation between the first response given to first contributions and their future contribution. As a preliminary survey, we sampled a set of OSS projects from the npm ecosystem (NodeJs packages). Although there is a considerably large portion of the first contribution, i.e., 27.66% with mainly neutral first response. Our execution plan includes both qualitative and quantitative approaches with three research questions. First, we inspect the first response

<sup>&</sup>lt;sup>1</sup>https://octoverse.github.com/

commented on 🔅 …					
This behaviour seems undesired. I'd rather we kept the current behaviour than follow npms current semantics.					
👍 З	🡎 23	😕 4			

Fig. 1: A screenshot example of a negative response to a new contributor. The new contributor may not further interact with this response or may not participate in future contributions.

TABLE I: Preliminary Dataset Statistics

<b>Contributions (Pull Req</b>	uests)
Total # of Projects	20
Total # of Contributions per Project	43,398
Min. # of Contributions per Project	674
Max # of Contributions per Project	5092
Min. # of First Contributions per Project	179
Max. # of First Contributions per Project	2024
% First Time Contributions	27.66% (out of 43,398)
Interactions (Comme	ent)
Total of Interaction in Pull Request	8,534
Min. # of Interaction per contribution	0
Max # of Interaction per contribution	111

of the first contributions. Second, we investigate the effects of characteristics of the first response to the interactions between first-time contributors to find the impact of future contributions.

#### **II. PRELIMINARY ANALYSIS**

The goal of the preliminary analysis is to manually explore whether sentiment analysis can be useful to detect the sentiment of a first response. Since communities are more likely to share the same terminologies and communication culture, we choose projects which belong to the npm ecosystem, which is one of the largest software ecosystems.

*a) Collected Dataset:* We collected a list of npm projects from two existing datasets (GHTorrent<sup>2</sup> and Libraries.io<sup>3</sup>). GHTorrent provides a mirror of git repositories and developer interactions gathered from GitHub<sup>4</sup>, while Libraries.io provides the meta-data and the relationships among packages that are hosted on popular software ecosystems, such as npm and Maven. There are over 1.3 million npm projects. Then, by adding a filter of only active projects (projects that contain at least one commit, pull request, or issues) in 2020, we are left with 11,127 projects.

For the preliminary study, we selected the top 20 npm projects with the most contributors. From this, we obtain 43,398 pull requests. We observed that 12,003 (27.66%) of pull requests are first contributions (i.e., created by the users who have never create any pull request in the project before), while only 8,534 (71.10%) of pull requests of first-time-contributions receive responses. There are 11,268 first-time contributors. Our dataset statistics are further displayed in Table I.

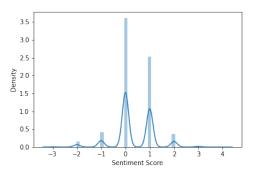


Fig. 2: The distribution of sentiment score of the first response to first contributions

b) Sentiment Analysis of First Response: As we plan to find the sentiment of the first responses, a sentiment analysis tool is needed. We selected SentiStrength-SE [8] as our sentiment analysis tools since it is the state-of-the-art tool for sentiment analysis of the software engineering-related text. We calculated the sentiment score of the first responses using SentiStrength-SE for our preliminary analysis. The tool receives a text as an input, and it then gives a sentiment polarity score of the given text. We applied the tool to the first responses and inspected the responses which their sentiment score are quite high and low. The output is ranged from a scale of -5, which refers to very negative sentiment, to 5, which refers to very positive sentiment.

**Distribution of sentiments.** We found that the sentiment score of the first responses is ranged from -3 to 4. The distribution of the sentiment score of the first responses is shown in Figure 2. To explore what kinds of words are in each score, we use keyword extraction tools to extract keywords from each sentiment score.<sup>5</sup> The results are shown in Table II.

We found that SentiStrength-SE can appropriately capture a positive sentiment since it captures many encouraging words, e.g., 'Excellenct,' 'Nice attempt' and 'Great job.' However, in the negative sentiment, keywords do not directly show displease words. We have also looked into the actual responses and found some examples of the high and low sentiment scores. We found that encouraging phrases, e.g., 'Excellent' and 'Thank for doing this' is normally in the text with high sentiment score; and phrases such as 'I don't like this,' 'This is not good,' etc. are in the text with a low sentiment score.

<sup>5</sup>https://monkeylearn.com/keyword-extractor-online/

<sup>&</sup>lt;sup>2</sup>https://ghtorrent.org/

<sup>&</sup>lt;sup>3</sup>https://libraries.io/

<sup>&</sup>lt;sup>4</sup>https://github.co.jp/

TABLE II: Keywords from the First Response

Sentiment Score	Keyword
-3	movies, odd whitespace changes, lodash, changes, accent colour, git novice, wrong branch, design changes, better way, visual changes
-2	mithril, user agent reporting, early next week, code, changes, way, minutes, thing, screencap stuff, fork tests
-1	error, obscure edge cases, data, deserialize, later today, return JSON.parse, mon Magazine, code size, Rookie mistake, contrived example
0	double colon, docs task, foo, corresponding object key, route parameter syntax, m.request url option variadic function syntax, super intuitive syntex, minimal test case, keys
1	Thanks, catch, pull request, nice work, SCSS, origin/next, work, site
2	Thanks, custom date formatting, first browserify package, minor comments, Thanks Jeremy, good cleanup, first pass, Great work, pull request, gulp file
3	Thanks, simple registered elements, something, good catch, async data-dependencies, Nice attempt, extended elements, Great job, userLand, redaw.strategy
4	Excellent, Wow

**Summary:** Preliminary analysis shows that most first responses are neutral. For keywords and phrases, encouraging phrases, e.g., 'Excellent' and 'Thank for doing this' appear with a high sentiment score. Differently, phrases such as 'I don't like this', 'This is not good', etc. appear with a low sentiment score.

### **III. STUDY PROTOCOLS**

In this section, we present the design of our study. This section includes data selection, sanity check, and the preparation of research questions with their motivation.

*a) Data Selection:* To generalize the results, we will perform our full experiment on Hata et al. [9] dataset, which contains a list of many open-source software projects in seven well-known programming languages, e.g., C, C++, Java, JavaScript, Python, PHP, Ruby. There is a total of 29,234 repositories in the dataset. The pull request will be extracted from the projects. We will select only closed pull requests as our dataset to ensure the correctness of the result. Since we investigate the contributors, we also consider the threat of multiple GitHub alias and bots. Hence, we adopt an identity merging bot detection tool to mitigate these threats. For identity merging, we follow approaches similar to Fry et al. [10] and also adopt bot detection techniques Golzadeh et al. [11].

b) Sanity Check: We will use the SentiStrength-SE, Sarker et al. [12] toxicity detection tools, EmoTxt[13] to investigate the characteristics of the first response. Even though the tools are well trained on the Software Engineering-related dataset, we would like to ensure the validity of the tools when applying them to our dataset. Hence, we will perform a sanity check on the three tools. The processes of the sanity check are as follows: We will sample the first responses that are positive, negative, and neutral by the score given by the sentiments, toxicity, and emotions. To ensure the significance of the sample, we will determine the sample sizes by using a confidence level of 95% and a confidence interval of 5%.<sup>6</sup> Then, three of the authors will perform the manual validation of each type of sentiment score. To calculate the interrater agreement between the manual classification results of the three authors, the Cohen's kappa[14] approach will be adopted. We will then report the precision, recall, F1 score, and AUROC (Area Under the ROC Curve) of the tools with our manual classification's kappa agreements score.

c) Research Questions: To guide our research towards the goal, we designed the following research questions:

**RQ1:** What are the characteristics of the first responses toward first contributors? Our motivation for the first research question is to understand the first response's characteristic to the first contributions in terms of sentiment, responsiveness, toxicity, and emotion of the response. The definition and extraction procedure of each characteristic will be explained in Section IV. The first response is the first comment on a pull request. As for baseline, we will compare the characteristic of the first response of the first contributions and ones of non-first contributions. We envision that this analysis will reveal insights on whether there are biases against the first pull request. Our assumption is that:

**H1.1:** First contributions are more likely to get positive responses compared to non-first contributions. Since the community tries to attract more contributors, we can expect that the community gives positive responses to the first contributions.

**H1.2:** First contribution are more likely to get more responsive responses compared to non-first contributions. Similar to H1.2, we expect that the community gives responsive responses to the first contributions.

**H1.3:** There are biases in giving toxic responses between first contribution and non-first contribution. Similar to H1.1, we expect that the community will be bias in giving the first response to the first contribution in terms of toxicity.

**H1.4:** Each emotion type is not evenly distributed in first contributions and non-first contributions. Similar to H1.1, we expect that the emotion in the first responses of the first contribution will be different from the ones of the non-first contribution. For example, there could be a 'surprise' emotion when first-time contributors make a huge contribution to the project while it seems normal to non-first-time contributors.

**RQ2:** What is the relationship between receiving a positive response and further interactions in the same pull request for a first-time contributor? Our motivation for the second research question is to understand whether the first responses affect future interactions between first-time contributors and project contributors. In this study, we

<sup>&</sup>lt;sup>6</sup>https://www.surveysystem.com/sscalc.htm

consider comments on pull requests as interactions between contributors. We expect that this analysis will reveal the effects of the first responses upon the first-time contributors. Our assumption is that:

**H2.1:** First-time contributors are more likely to interact with non-first-time contributors after the first responses when they receive positive responses. Since receiving positive responses encourage the first-time contributors' willingness to collaborate [15], we can expect that the first-time contributors will be likely to interact afterward.

**H2.2:** First-time contributors are more likely to interact with non-first-time contributors after the first responses when they receive responsive responses. As receiving a responsive response can keep the first-time contributors' attention, i.e., the first-time contributors do not wait too long, we can expect that the first-time contributors will interact with others when receiving responsive responses.

**RQ3:** What is the relationship between first-time contributors' interactions and their future contributions? Answering this research question will provide us with insights into factors that affect the future contributions of first-time contributors. This possibly leads to potential solutions to avoid first-time contributors abandon OSS projects.

### IV. EXECUTION PLAN

We plan to use both qualitative and quantitative approaches to answer our research questions.

### A. Research Method for RQ1:

For the first research question, we plan to use a quantitative method. We will separate contributions into two groups: the first contribution and the non-first contribution. The characteristics of the first responses of both groups will be separately extracted. To extract the sentiment of the first responses, we plan to use SentiStrength-SE [8], the state-of-the-art sentiment analysis tool for software engineering text. The tool can be used to determine the scale of the polarity score of the responses. The sentiment score is ranged from -5 (very negative) to 5 (very positive). For the responsiveness of the first responses, we will extract the duration between the creation of the pull requests and the time when the first comment is posted. For toxicity detection, we will adopt Sarker et al. [12] tool. This tool is a binary classification tool that receives text as the input, and it then reports whether the text contains toxicity or not. For emotion detection, we will use EmoTxt [13]. This tool is a binary classification tool that receives text as the input. It then classifies the existence of the emotion in the text. The supported emotion is "Love," "Joy," "Surprise," "Anger," "Sadness," and "Fear."

a) Analysis Plan: To analyze the result of the RQ1, we plan to compare the sentiment and the responsiveness between the first contribution and non-first contribution group to answer the H1.1 and H1.2. We will report the result in the box plots. The box plots will show the difference in the distribution of sentiment score/responsiveness of the two groups. For the H1.3 and H1.4, we will report the number of first responses classified as Toxicity and each emotion in a table.

b) Significant Testing: Before applying the statistical test, we will inspect the data to see whether it is normally distributed or not. This will allow us to select a suitable test. To test normality, we will adopt Shapiro-Wilk test [16] with alpha = 0.05. For example, we will perform a Shapiro-Wilk test on the first responses' sentiment score to first contributions and non-first contributions. If we receive a p-value greater than 0.05, it will imply that the distribution of the sentiment score is not significantly different from the normal distribution. In other words, we can assume normality. If sentiment in the two groups' first responses is normally distributed, we will select a two-tailed independent t-test with alpha = 0.05. This is because our sample group, which are first contributions and non-first contributions, are independent. In case when the data of the two groups are not normally distributed, we will adopt a two-tailed Mann Whitney U test [17] with alpha = 0.05. This is because it is a non-parametric statistical test, and there is no normality assumption. The test will be performed on the followings hypothesis to answer H1.1 and H1.2:

 $H1.1_{null}$ : There is no difference between the sentiment score of the first response of first contributions and non-first contributions.

 $H1.2_{null}$ : There is no difference between the responsiveness of the first response of first contributions and non-first contributions.

We plan to investigate the effect size. The different methods are needed according to whether the data of the two groups are normally distributed or not. We will use Hedges g effect size [18], which is a parametric test, to measure the effect size if the data is normally distributed. Effect size is analyzed as follows: |d| < 0.2 as "negligible", |d| < 0.5 as "small", |d| < 0.8 as "medium", otherwise "large". If the data are not normally distributed, we will apply Cliff's  $\delta$ , which is a nonparametric effect size measure (Romano et al, 2006). Effect size is analyzed as follows: (1)  $|\delta| < 0.147$  as Negligible, (2)  $0.147 \le |\delta| < 0.33$  as Small, (3)  $0.33 \le |\delta| < 0.474$  as Medium, or (4)  $0.474 \le |\delta|$  as Large. To analyze Hedges g and Cliff's  $\delta$ , we use the *effsize* R package.<sup>7</sup>

We need different statistical test for H1.3 and H1.4 because the dependent variables, i.e. toxicity and emotion, are categorical. Thus, we will use Pearson's chi-squared test  $(X^2)$  [19] to test the following hypothesis to answer H1.3 and H1.4:

 $H1.3_{null}$ : Toxicity is evenly distributed in the first response to the first contributions and non-first contributions.

 $H1.4_{null}$ : Each emotion type is evenly distributed in the first responses to the first contributions and non-first contributions.

### B. Research Method for RQ2:

For RQ2, we plan to use both qualitative and quantitative approaches. The first-time contributors will be separated into 2 groups: ones that interacted with project contributors and ones that did not interact with project contributors in their first contributions. As for the group separation criteria, we consider the first contributions interacted with project contributors if

<sup>&</sup>lt;sup>7</sup>https://cran.r-project.org/web/packages/effsize/

they responded at least once after receiving the first response; otherwise, we consider them as no interaction.

*a) Analysis Plan:* The sentiment and the responsiveness of the first responses will be used to compare between two groups. Similar to RQ1, we will report results in the box plots. Furthermore, we will incorporate a qualitative analysis to reveal reasons for negative responses. To do this, we will first select a sample of the negative responses. We will determine the sample sizes using a confidence level of 95% and a confidence interval of 5%. Then, we perform our qualitative analysis of the reason for each negative response by following the card sorting method as in Li et al. [20]. Furthermore, we report the kappa agreement score.

b) **Significant Testing**: In order to statistically validate the differences between the two groups, i.e., ones that interacted with project contributors and ones that did not interact with project contributors in their first contributions, we plan to perform the same statistical test as *H1.1* and *H1.2*. The test will be performed on the followings hypothesis:

 $H2.1_{null}$ : There is no difference between the sentiment score of the first response of the first-time contributors that interacted with project contributors and one that did not interact

 $H2.2_{null}$ : There is no difference between the responsiveness of the first response of the first-time contributors that interacted with project contributors and one that did not interact.

As same as RQ1, we investigate effect size using Cliff's  $\delta$ .

# C. Research Method for RQ3:

For RQ3, we plan to use a quantitative method. As we would like to see the correlation between the interactions between first-time contributors and project contributors and future contributions. We will train classification models, e.g., logistic regression, random forest, and SVM. The model will train on independent variables by leveraging dependent variables. The followings are the variables that mainly capture the characteristics of the first-time contributors' interaction that we focus on: (1) Sentiment of First Response: We will extract this variable by using SentiStrength-SE [8] as same as in RQ1 and RQ2. (II) Responsiveness of First Response : This variable will be calculated as the duration between the pull request creation date and the first response. (III) *Number of interactions* : We plan to calculate this variable by considering the total number of comments on a pull request. More specifically, we will count the number of comments that were written after the first response until the last comment of the first-time contributors on the pull request. (IV) Number of Words in the First Response: This variable is the total words in the first response. (V) Result of the Pull Request: This is a binary variable that shows whether the pull request is merged or not. (VI) Existence of toxicity in the First Response: This is the binary variable that shows whether the first response contains toxicity or not. (VII) Emotion in the First Response: As the EmoTxt allows us to detect each emotion separately, we will consider six binary variables which describe the emotion in the first response. For example, "Anger" will be a binary variable in the first response.

Since contributing to OSS projects contains much more dimensions of factors than the first response's dimension, we will incorporate other dimensions of factors as well. **Contributors Dimension** variables will be the variables that capture the contributors-side characteristic, e.g., first-time contributors' experience. **Project Dimension** variables will capture the project-side characteristic, e.g., project-size related features. **Contribution Dimension** variables will capture the contribution-side characteristic, e.g., size of the contribution.

The dependent variable is the *Future Contribution*. This variable is binary that shows whether a first-time contributor makes a future contribution. In order to determine whether the first-time contributor will continuously contribute or not, we will inspect the time between the first and next contribution (i.e., submitted pull request) of the first-time contributor in each dataset. We then select the maximum days as the threshold to consider that the first-time contributor has left the project.

1) Analysis Plan: Firstly, we will inspect how well each model fits the data. We will apply 10-fold cross-validation and report the precision, recall, F1 score, and AUROC (Area Under the ROC Curve) of each model. Then, we will select the best suitable model for the feature importance analysis. We will apply feature permutation importance to see how much the model depends on each variable. <sup>8</sup> By doing this, we will be able to compare the feature importance between the first-time contributors' interaction variables against the other dimension of features. To see how each variable is associated with *Future Contribution*, we will calculate pairwise correlations. Then, we will report and plot the correlation matrix in a heatmap.<sup>9</sup>

#### V. IMPLICATIONS

We summarize our implications for the key stakeholders:

**OSS Projects** Our findings will bring insights into how the interaction between first-time contributors and project contributors in OSS projects affects future contributions of the first-time contributors. We believe that fast and appropriate responses to first-time contributors are needed to attract future contributions to OSS projects. Automated tools, e.g., bots, could promptly give appropriate responses to contributors when they make pull requests or could notify project contributors when they are likely to give negative responses.

**Researchers** This study will reveal interaction-related factors matter for future contributors and to what extent does the factors affect OSS projects' contributions. First-time contributors-related future studies should consider and could further investigate these factors in other proprietary industries, such as Nonprofit Organization (NPO) and OSS projects. Implementing tools such as bots that automatically send the first responses to first contributions and contributors and measure the sentiment of responses could be useful for future studies.

<sup>&</sup>lt;sup>8</sup>https://scikit-learn.org/stable/modules/permutation\_importance.html

<sup>&</sup>lt;sup>9</sup>https://seaborn.pydata.org/examples/many\_pairwise\_correlations.html

**Contributors** This study helps contributors to understand how important their interactions are. They should consider the response sentiment and response time in the review process since the discussion on pull requests can explicitly affect others' contribution intention and the number of first contributions.

#### VI. THREATS TO VALIDITY

We summarize four key threats. (1) Multiple Identity. To deal with multiple GitHub account, we will adopt an identity merging technique to mitigate this threat similar to Fry et al. [10]. (II) Bots. Bots [21] may threaten our calculation of text analysis, e.g., sentiment, toxicity, and emotion. We mitigate this by adopting a tool to identify bots in the OSS projects [11]. (III) No Response Pull-request Selection Process. To mitigate incorrectly no response pull-requests, we will filter out ongoing pull-request and left only closed pull-request. (IV) No Future Contribution Selection Process. To mitigate the incorrectly identified "no future contribution" status of the first-time contributors, we plan to leave a time window for a selected pull request.

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