

## Understanding the Role of External Pull Requests in the NPM Ecosystem

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**Abstract** The risk to using third-party libraries in a software application is that much needed maintenance is solely carried out by library maintainers. These libraries may rely on a core team of maintainers (who might be a single maintainer that is unpaid and overworked) to serve a massive client user-base. On the other hand, being open source has the benefit of receiving contributions (in the form of External PRs) to help fix bugs and add new features. In this paper, we investigate the role by which External PRs (contributions from outside the core team of maintainers) contribute to a library. Through a preliminary analysis, we find that External PRs are prevalent, and just as likely to be accepted as maintainer PRs. We find that 26.75% of External PRs submitted fix existing issues. Moreover, fixes also belong to labels such as **breaking changes**, **urgent**, and **on-hold**. Differently from Internal PRs, External PRs cover documentation changes (44 out of 384 PRs), while not having as much refactoring (34 out of 384 PRs). On the other hand, External PRs also cover new features (380 out of 384 PRs) and bugs (120 out of 384). Our results lay the groundwork for understanding how maintainers decide which external contributions they select to evolve their libraries and what role they play in reducing the workload.

**Keywords** Third-party libraries, Pull Requests, OSS sustainability, Software Ecosystems

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## 1 Introduction and Motivation

Third-party libraries provide a means by which software teams can quickly build an application, avoiding the need to start from scratch. Popular usage has led to the explosion of third-party library inter-connecting networks of dependencies that form large ecosystems (Islam et al, 2021; Decan et al, 2018; He et al, 2021). For example, the NPM ecosystem of libraries (aka packages) is a critical part of the JavaScript world, with open source contributions from hundreds of thousands of open source developers and maintainers. Evidence of its impact was its purchase by Microsoft’s GitHub in early 2020 (Friedman, 2020). Despite their popularity, libraries are prone to maintenance and evolution issues. In particular, threats such as vulnerabilities (Chinthanet et al, 2021; Durumeric et al, 2014) and transitive dependency changes (Dey et al, 2019) may cause a library to risk becoming obsolete (Kula et al, 2018), or worse, pose an important security risk.

Recent events such as the Log4Shell vulnerability (Nichols, 2022; Berger, 2021) and the faker sabotage (Sharma, 2022) illustrate concerns about how maintainers become overwhelmed with their workload. This is especially the case when there is a small core maintainer team (sometimes a single maintainer) that is depended upon by a massive user base. For instance, it was reported that *‘a developer of two popular libraries, decided to inject malicious code into them, citing that the reason behind this mischief on the developer’s part appears to be retaliation—against mega-corporations and commercial consumers of open-source projects who extensively rely on cost-free and community-powered software but do not, according to the developer, give back to the community’* (Roth, 2022). Another example is when the maintainers of a vulnerable library expressed their frustration when maintaining a library in a tweet, *‘... maintainers have been working sleeplessly on mitigation measures; fixes, docs, CVE, replies to inquiries, etc. Yet nothing is stopping people to bash us, for work we aren’t paid for, for a feature we all dislike yet needed to keep due to backward compatibility concerns...’* (Yazıcı, 2021).

Recent initiatives such as the Alpha-Omega project allow industry (Google and Microsoft) to partner with maintainers to systematically find and fix vulnerabilities that have not yet been discovered in open source code (OpenSSF, 2022). Although these critical contributions are indeed significant, little is known about the other external contributions that these libraries constantly receive from the ecosystem. Although prior work shows that external contributions are needed, analysis is at a higher level of granularity. For instance, Samoladas et al (2010) show that OSS projects require a constant stream of contributions, while Nakakoji et al (2003) and Raymond (1999) depict external contributions as more casual contributions. In this light, it is unknown how external contributions ease maintainer workload, and how they differ from maintainer contributions (i.e., fixing bugs, new features, documentation, etc.).

In this study, we analyze contributions submitted as Pull Requests (PRs) in the NPM ecosystem. Based on prior work (Valiev et al, 2018), we classify a PR contribution based on the access level (i.e., can merge a PR into the code

## Add syntax option to trim insignificant zeros #57

Merged mboostock merged 14 commits into d3:master from vasturiano:trim-insignificant-zeros on May 9, 2018

Conversation 7   Commits 14   Checks 0   Files changed 10

vasturiano commented on May 8, 2018

This PR solves #54.

It introduces a new option ( `t` ) in the specifier syntax that enables trimming of insignificant zeros across all format types.

Fig. 1: An External PR which is linked to an issue using the keyword *solves*.

base) of the submitter. In other words, we define an External PR as a PR submitted by a contributor who is not a maintainer, such as the example shown in Figure 1 where a contributor submits a PR that solves an already existing issue. In contrast, an Internal PR is a PR submitted by a maintainer. Finally, a Bot PR is a PR submitted by an automated bot such as dependabot.<sup>1</sup> We collect 1,076,123 PRs from 47,959 NPM packages to first conduct a preliminary study. The results indicated that External PRs are indeed prevalent with a large number being received by a NPM package (75.02% on average). Furthermore, NPM contributors have a high (88.87% on average) rate of submitting External PRs. We find that on average, External PRs' (55.65% per package) acceptance is higher than Internal PRs' (51.04% per package). Encouraged by these results, and to further explore the role of External PRs, we carried out an empirical study to answer these two research questions:

- **(RQ1) To what extent do External PRs ease maintainer workload by fixing existing issues?** Our motivation for this research question is to confirm the extent to which External PRs fix an issue that is already part of the maintainers' workload.
- **(RQ2) How different are the code changes when comparing External PRs to Internal PRs?** For a qualitative understanding of External PRs, for this RQ, we extract and compare External PRs with Internal PRs.

The results of RQ1 show that 26.75% of External PRs submitted to a package are linked to an already existing issue. Furthermore, we find evidence that there are External PRs that require the attention of the core team (e.g., referencing breaking changes, urgent, and on-hold labels). For RQ2, similar to other PR types (internal and bots), we find that External PRs are most likely to contain changes to add new features (170 out of 384 PRs) to a package. However, different to Internal and Bot PRs, External PRs tend to focus on documentation (44 out of 384) as opposed to features (380 out of 384) for bots, and refactoring (34 out of 384) for Internal PRs.

The rest of the paper is organized as follows. Section 2 provides the data preparation processes for our datasets and the preliminary study. Section

<sup>1</sup> <https://github.com/dependabot>

3 provides approach and findings for each RQ. Section 4 discusses lesson learnt from our work. Section 5 exposes potential threats to validity. Section 6 reviews previous studies related to our study. Section 7 concludes the paper. We provide a replication dataset that includes all our scripts, tools and datasets for researchers to use in the future at: <https://github.com/NAIST-SE/External-PullRequest>.

## 2 Data Preparation and Preliminary Study

In this section, we present our data preparation and preliminary study.

### 2.1 Data Collection

As shown in Figure 2, we separate our data collection process into three stages.

*Stage One - Data Collection.* For this study, we have two data sources to construct our dataset. The first data source is the NPM registry which contains a listing of the available NPM packages. We select the NPM packages due to their popularity (cf. Section 1) and having been the subject of many studies (Chinthanet et al, 2021; Cogo et al, 2019; Decan et al, 2018; Abdalkareem et al, 2017; Zerouali et al, 2018; Dey et al, 2019; Dey and Mockus, 2020). Following related work, we obtained this listing following the method of Chinthanet et al (2021), ending up with 107,242 original NPM packages. The second data source is for obtaining the PR information. For this, we use the GitHub API<sup>2</sup>. We obtained 1,076,123 PRs from 47,959 packages. Note that we filter out packages that do not have any PR (i.e., 8,991 packages with no dependencies and 67 packages had no PRs submitted), to ensure that our dataset contains active packages with PRs. The collected PRs contain the PR information, e.g., PR title, description, status, label, and code patches.

To ensure a quality dataset, we further filter out libraries that have no other library depending on them. This filter ensures that each package meets the minimum requirements for our analysis. In the end, we obtained 945,921 PRs from 38,925 packages. Data collection was performed in January 2021. The summary statistics of the collection process are shown in Table 1.

*Stage Two - Data classifying for quantitative analysis (Classified Dataset).*

In this stage, we classify whether a PR is an External PR, an Internal PR, or a Bot PR. As shown in Table 1, by identifying the 116,265 contributors to the 945,291 PRs, we find that 290,552 (i.e., 30.74%) of the filtered PRs are External PRs, while 340,465 or 36.02% of the filtered PRs are Internal PRs. To identify Bot PRs, in addition to parameters from the GitHub REST API, we follow prior work proposed by Dey et al (2020) and Golzadeh et al (2020), to collect a list of bots provided by GitHub. After performing this classification

<sup>2</sup> <https://docs.github.com/en/rest/reference/pulls#get-a-pull-request>

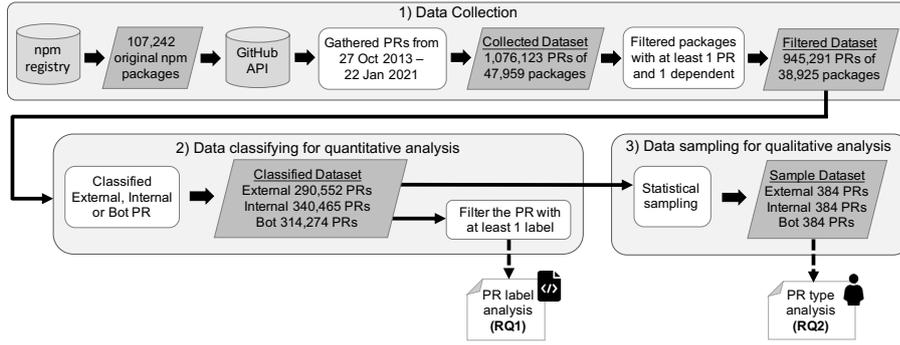


Fig. 2: Overview of the data preparation. It consists of three stages: (i) Data collection, (ii) Data classifying for quantitative analysis for RQ1, and (iii) Data sampling and qualitative analysis for RQ2

Table 1: Statistics of the collected dataset and filtered dataset (after stage 1: Data collection), and classified dataset (after stage 2: Quantitative classifying)

<b>Collected Dataset</b>	
Repository snapshot	27 Oct 2013 — 22 Jan 2021
# original NPM packages	107,242
# collected NPM Packages	47,959
# NPM Pull Requests	1,076,123
<b>After Filtering Process</b>	
# NPM Packages	38,925
# NPM Pull Requests	945,291
# contributors	116,265
<b>Classified Dataset (RQ1)</b>	
# Bot PR	314,274 (33.24%)
# External PR	290,552 (30.74%)
# Internal PR	340,465 (36.02%)
<b>Sample Dataset (RQ2)</b>	
# Pull Requests	1,152

as shown in Table 1, we identified 314,274 Bot PRs from the filtered dataset. A summary of the detected bots is shown in Table 2.

*Stage 3. Data sampling for qualitative analysis (Sample Dataset).* From the classified dataset obtained in Stage 2, we draw a statistically representative random sample of 384 External PRs, 384 Internal PRs, and 384 Bot PRs. These sample sizes allow us to generalize the conclusions about the ratio of PRs with a specific characteristic to all studied PRs with a confidence level of

Table 2: Summary of Bots detected

bot name	# PR
greenkeeperio-bot	114,945 (36.57%)
dependabot-preview[bot]	67,933 (21.62%)
greenkeeper[bot]	62,837 (19.99%)
renovate[bot]	36,796 (11.71%)
dependabot[bot]	25,339 (8.06%)
others	6,424 (2.05%)
Total	314,274

95% and a confidence interval of 5%, as suggested by a prior work Hata et al (2019) and using the calculator.<sup>3</sup>

## 2.2 Preliminary study

To understand the impact of External PR, we first want to explore the extent to which NPM packages receive PRs from external contributors, and how many External PRs are submitted by contributors. We then study the extent to which library maintainers accept External PRs. Hence, we ask the following three preliminary questions.

**(A1) From a Package Perspective Approach:** We first identify the proportion of External PRs in relation to all submitted PRs. We define the proportion of the External PRs of a package and submitted by a contributor as follows. For an NPM package `pkg` and a contributor `contrib`, we calculate the proportion as:

- **Ext-PRrate (pkg):**  $\frac{\#ExternalPR}{\#all-PR}$  submitted to a `pkg`. In this case, a higher proportion means that there are more External PRs received by that package.

where `all-PR` is the sum of PRs (External PRs, Internal PRs, Bot PRs) per package. For statistical validation, we apply Spearman’s rank correlation coefficient or Spearman’s  $\rho$ , a non-parametric measure of rank correlation, to analyze the correlations between the number of External PRs. Spearman’s  $\rho$  value ranges from -1 to 1. We analyze as follows: (1)  $|\rho| < 0.20$  is Negligible or no relationship, (2)  $0.20 \leq |\rho| < 0.30$  is Weak positive/negative relationship, (3)  $0.30 \leq |\rho| < 0.40$  is Moderate positive/negative relationship, (4)  $0.40 \leq |\rho| < 0.70$  is Strong positive/negative relationship, (5)  $0.70 \leq |\rho| < 1$  is Very strong positive/negative relationship, or (6)  $|\rho| = 1$  is Perfect relationship.

**Results:** From the perspective of a package, we discuss two findings. The first finding is that, from Figure 3a, we show visually that External PRs are indeed prevalent, as shown by the high Ext-PRrate (pkg). The findings show that on average, 75.02% of PRs received by NPM packages are External PRs.

<sup>3</sup> <https://www.surveysystem.com/sscalc.htm>



(a) The proportion of External PRs a package received (Ext-PRrate (pkg)), i.e., mean of 75.02%

(b) The proportion of External PRs a contributor submitted (Ext-PRrate (contrib.)), i.e., mean of 88.87%

Fig. 3: Prevalent of Packages Receiving an External PR showing in (a) and Contributor submission an External PR showing in (b).

**(A2) From a Contributor Perspective Approach:** Similar to A1 we identify the proportion of External PRs in relation to all submitted PRs. However, we now define the proportion of External PRs submitted by a contributor as follows. For an NPM package `pkg` and a contributor `contrib.` we calculate the proportion as:

- **Ext-PRrate (contrib.):**  $\frac{\#ExternalPR}{\#all-PR}$  submitted by a `contrib.` In this case, a higher proportion means that there are more External PRs submitted by a contributor. Our statistical validation is the same as P1.

**Results:** Similar to the package perspective, we discuss two findings for the analysis of contributor submissions of External PRs. The first finding is that, from Figure 3b, we confirm visually that a high percentage of contributions submitted by a contributor are External PRs. This is evident by an average of 88.87% being External PRs per contributor.

**(A3) Acceptance Ratios Approach:** We identify whether or not there is a difference in how External PRs are accepted. To do so, we classify the different state changes of a PR. Similar to prior work Wang et al (2021), there are several states of a PR, that is Accepted PR – where the PR has been closed and merged, and Abandoned PR – where the PR has been closed but has not been merged. After identifying the state of each PR, we performed two analyses. It is important to note that a PR can be either open or closed, merged or not merged. Hence, since we are only concerned with acceptance (closed and merged) and abandonment (closed and not merged), we ignore other state (open and not merged). Similarly to RQ1, we calculate the distribution of acceptance at the package level of analysis. Hence, we use proportions as follows:

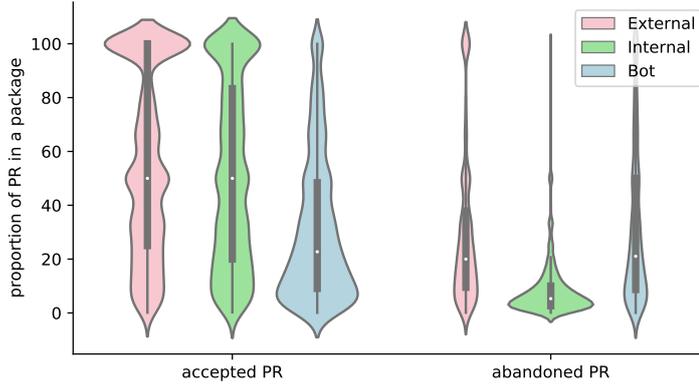


Fig. 4: Distributions of PR state by the type of PR. Note that External (Pink), Internal (Green), and Bot (Blue) PRs are shown separately.

- **state-External**  $\text{PR}(x)$ :  $\frac{\#state-ExternalPR}{ExternalPR}$  that is submitted to a `pkg`. A higher proportion indicates that External PRs have a higher acceptance or abandonment rate for that package.
- **state-Internal**  $\text{PR}(x)$ :  $\frac{\#state-InternalPR}{InternalPR}$  that is submitted to a `pkg`. A higher proportion indicates that Internal PRs have a higher acceptance or abandonment rate for that package.
- **state-Bot**  $\text{PR}(x)$ :  $\frac{\#state-BotPR}{BotPR}$  that is submitted to a `pkg`. A higher proportion indicates that Bot PRs have a higher acceptance or abandonment rate for that package.

where  $x$  refers to either an accept or abandon state. Using these metrics, the first analysis is the distribution of the External PRs that were eventually accepted. We test the following null hypothesis:

- $H2.1_{null}$  *There is no difference between the acceptance and abandonment of External PRs*

Similarly to P1 and P2, we use the Mann-Whitney test to test statistical significance. We also measure the effect size using Cliff’s  $\delta$ , a non-parametric effect size measure (Cliff, 1993). The effect size is analyzed as follows: (1)  $|\delta| < 0.147$  as Negligible, (2)  $0.147 \leq |\delta| < 0.33$  as Small, (3)  $0.33 \leq |\delta| < 0.474$  as Medium, and (4)  $0.474 \leq |\delta|$  as Large. We use the `cliffsDelta`<sup>4</sup> package to analyze Cliff’s  $\delta$ . For the second analysis, we compare the distributions between the three different PR types (External PR, Internal PR, Bot PR). For statistical validation, we test the following hypothesis:

- $H2.2_{null}$  *There is no difference in PR acceptance between external, internal or bot PRs*

First, we apply the Kruskal-Wallis H-test (Kruskal and Wallis, 1952), which is a non-parametric statistical test to use when comparing more than two

<sup>4</sup> <https://github.com/neilernst/cliffsDelta>

Table 3: Summary statistics of each PR states of External PR, Internal PR, Bot PR i.e., Mean, Median, and SD.

PR	% PR per pkg		
	Mean	Median	SD
state-External PR(accept)	55.65%	50.00%	33.88%
state-Internal PR(accept)	51.04%	50.00%	33.54%
state-Bot PR(accept)	30.94%	22.73%	26.78%
state-External PR(abandon)	29.36%	20.00%	27.19%
state-Internal PR(abandon)	8.29%	5.31%	9.53%
state-Bot PR(abandon)	31.18%	21.05%	28.10%

Table 4: Statistical test of External PR acceptance ratios

External PR	Cliff's $\delta$
state-External PR(accept) > state-External PR(abandon)*	medium

Mann-Whitney U with \*:p-value < 0.001

Table 5: Contingency table showing Dunn's test and Cliff's  $\delta$  between Internal PR, External PR, and Bot PR

	Cliff's $\delta$ (accept state   abandon state)	
	External PR	Internal PR
External PR	-	negligible*   large*
Internal PR	-	medium*   negligible
Bot PR	-	medium*   large*

Dunn test \*:p-value < 0.001

groups. If there is significance, we then will conduct the Dunn test (Dinno, 2015) to determine exactly which type of PRs are different to External PRs. Additionally, we measure effect size using Cliff's  $\delta$ .

*Results:* Figure 4 shows the acceptance ratios of all PR types per NPM package. Note that the pink violin plot highlights the external PRs, split into accepted and abandoned rates. Visually, we can see that both shapes are different. In terms of the accepted External PRs, we can see that the violin plot has a heavy top shape, indicating that there are many packages in the 90 to 100 percent ratio. On the other hand, looking at the abandoned ratio, we see that the violin plot is much thinner. Complementary to the visual results, Table 3 shows that statistically, External PRs have a 55.65% likelihood on average to be accepted. On the other hand, the chances for an External PR to get abandoned is also lower, with a 29.36% chance on average. For statistical validation, Table 4 confirms that there is indeed a statistical difference and confirms that  $H2.1_{null}$  *There is no difference between the acceptance and abandonment of External PRs* is accepted with a medium effect size.

Returning to Figure 4, we can also compare External PRs against the other PR types (i.e., Internal PR and Bot PR). Interestingly, we can identify two findings. The first is that the shape of the violin plots of External PRs

and Internal PRs are almost identical, with Bot PRs being different in terms of acceptance. Complementing this result, Table 3 supports this, with both internal and external PRs having the same 50% chance of being accepted. Different from this, the evidence suggests that Bot PRs are least likely to be accepted (i.e., 30.94% on average). However, when it comes to abandonment, External PRs and Internal PRs differ. As shown in both the violin plot and the statistics in Table 3, we see that developers are less likely to reject an Internal PR (8.29%) as opposed to an External PR (29.36). Similarly to External PRs, Bot PRs have the highest chance of being abandoned (31.18%). For statistical validation, Table 5 confirms that there is indeed a statistical difference and confirms that  $H2.2_{null}$  *There is no difference in PR acceptance between external, internal or bot PRs* is accepted.

**Preliminaries:** Findings indicate that External PRs are indeed prevalent with a large number being received by NPM packages (75.02% on average). Furthermore, NPM contributors have a high (88.87% on average) rate of submitting External PRs. We find that on average, External PRs' (55.65% per package) acceptance is higher than Internal PRs' (51.04% per package).

### 3 Empirical Study

Motivated by the results of the preliminary study, we are now able to understand the need for External PR.

#### 3.1 Approach

**To answer RQ1**, we conduct two analyses. For the first analysis, we assume that developers' attention will be caught by PRs that resolve existing issues raised in a library. Hence, we identify PRs that were created in response to an already existing issue that was raised in the library. To do so, we link PRs to issues, following the process explained in the GitHub documentation<sup>5</sup>. Concretely, we search for keywords (i.e., close, closes, closed, fix, fixes, fixed, resolve, resolves, resolved) in the description of the PR (cf. Section 2 for example). For our results, we will present statistics on the rate of PRs that can be linked to issues using proportions as follows:

- **Linked External PR:**  $\frac{\#Linked-ExternalPR}{\#ExternalPR}$  submitted to a pkg. In this case, a higher proportion means that there are more linked External PRs for that package.

<sup>5</sup> <https://docs.github.com/en/issues/tracking-your-work-with-issues/linking-a-pull-request-to-an-issue>

Table 6: Manually curated keywords of PR labels that ‘require attention’.

identified keywords in labels	
Require attention	attention, blocked, blocker, break, breaking, broken, change, confusing, critical, denied, density, difficult, difficulty, effort, exclamation, failed, failing, followup, hard, high, hold, important, incompatible, inconvenient, leak, memory, must, needed, notable, performance, prio, priority, required, risk, risky, securities, security, severity, urgent.
False positives	easy, low, medium, minor, no, non, review

- **Linked Internal PR:**  $\frac{\#Linked-InternalPR}{\#InternalPR}$  submitted to a `pkg`. In this case, a higher proportion means that there are more linked Internal PRs for that package.

Note that for this analysis, we decided not to report linked issues for Bots, due to a large amount of noise of keywords generated by the auto-generated messages that reference fixes outside of the project.

For the second analysis, we assume that a PR might be labeled with words that might grab the attention of any core member, for example, a PR to fix a potential breaking change. For this analysis, we first needed to filter out PRs that did not contain any labels. From the classified dataset, we ended up with 245,693 (78.18%) Bot PRs, 26,797 (9.22%) External PRs and 50,144 (14.73%) Internal PRs containing a label. Once we collected the PRs with labels, we performed three steps as part of pre-processing the labels. In the first step, we remove non-textual symbols such as emojis, punctuation, and other non-English characters from the labels. For the second step, we tokenize the label so that similar words can be grouped together. Finally, in our last step, we apply lemmatization to derive the common base form. For the implementation, we used the Python packages `re`<sup>6</sup> and `nlTK`<sup>7</sup>.

Table 6 shows the curated list of keywords used to identify labels that would raise the attention of the core team. Following related work (Mäntylä et al, 2017), we identified words that would raise the attention (arousal) with words that show the priority levels of a label. Using the base common words for each label, we then systematically and manually checked all unique common base labels to infer their importance. The analysis involved two authors who manually scanned the words to classify keywords together, with one pointing out a label then the other mutually agreeing, similar to Subramanian et al (2022). Furthermore, to remove false positives (such as the label ‘low severity’), we also collected a list of non-critical keywords. We will report the percentage of these labels for all PR types (i.e., External PR, Internal PR, and Bot PR). Furthermore, we will report the number of PRs and also the top five labels within each type of PR.

<sup>6</sup> <https://pypi.org/project/re/gex/>

<sup>7</sup> <https://www.nlTK.org/>

**To answer RQ2**, we perform a qualitative analysis to characterize the differences in PR types between Internal PRs, External PRs, and Bot PRs. In particular, we manually classify the sample PRs based on the taxonomy of Subramanian et al (2022) as defined below:

- *Documentation*: Changes and additions made to documentation files such as READMEs and/or comments explaining code. Note: Only PRs, where the majority change is documentation, are classified as documentation change.
- *Feature*: Adding new functionality/features to the project. Following Subramanian et al (2022), we consider dependency updates as a feature change.
- *Bug*: Fixing unexpected behaviour in code.
- *Refactoring*: Restructuring code to make it more understandable/readable and/or conform to coding standards.
- *GIT related issues*: Solving merge conflicts, adding elements to .gitignore files and other changes related to GIT.
- *Test cases*: Adding test cases and/or adding code to facilitate testing.
- *Other*: Anything that does not fall into the above categories.

We conducted manual coding to classify our sample PRs, a technique that is popular in various qualitative studies of software engineering (Wattanakriengkrai et al, 2022). First, three authors of this paper independently coded the PR types for 45 samples (i.e., containing 15 from External PR, Internal PR, and Bot PR) in a first iteration. They consider the PR title, description, conversation, and code changes. We then calculated the inter-rater agreement between the categorization results of the first three authors using Cohen’s kappa (McHugh, 2012). The kappa agreement varies from 0 to 1 where 0 is no agreement and 1 is perfect agreement. This process is iterated until there is a kappa agreement of more than 0.8 or “almost perfect” (Viera and Garrett, 2005).

For this analysis, we obtain a kappa agreements of 0.91 for overall (External PR, Internal PR, and Bot PR), 0.95 for External PR, 0.90 for Internal PR, and 0.95 for Bot PR in the second round of iterations. After this high agreement score, the remaining data in the samples of 384 Internal PRs, 384 External PRs, and 384 Bot PRs is divided into three parts, and each part is coded separately by three authors of the paper. We apply Pearson’s chi-squared test ( $\chi^2$ ) (F.R.S., 1900) to test whether content of PR to External PR and Internal PR are independent or not. To show the power of differences between each External PR and Internal PR, we investigate the effect size using Cramér’s V ( $\phi'$ ), which is a measure of association between two nominal categories (Cramér, 2016). According to Cohen (1988), our grouping has one degree of freedom ( $df^*$ ), hence, effect size is analyzed as follows: (1)  $\phi' < 0.07$  as Negligible, (2)  $0.07 \leq \phi' < 0.20$  as Small, or (3)  $0.30 \geq \phi'$  as Large.

### 3.2 Findings

In this section, we present our findings to answer our two research questions.

Table 7: Summary statistic of the linked External PR and linked Internal PR i.e., Mean, Median, and SD (RQ1)

PR	#linked PR	% linked-PR per pkg		
		Mean	Median	SD
Linked-External PR	22,662	26.75%	16.67%	25.68%
Linked-Internal PR	35,980	42.57%	33.33%	32.93%

Table 8: Ratio of PRs that were labeled as ‘require attention’.

	# PR with label	# PR attention label	# attention label
External PR	26,797	984 (3.63%)	166 (61.25%)
Internal PR	50,144	2,177 (4.34%)	205 (75.65%)
Bot PR	245,693	3,392 (1.38%)	26 (9.59%)
Total	322,634	6,553 (2.03%)	271 (100%)

Table 9: Top five attention unique labels of each PR type.

	Top five attention unique labels (#)
External PR	breaking (78), P3: important (50), P1: urgent (46), on hold (45), Breaking Change (40)
Internal PR	breaking (311), breaking change (141), P2: required (104), change/patch (96), performance (80)
Bot PR	security (3248), breaking (28), CH: Security (23), Type: Security (21), Security (11)

*PRs linked to existing issues.* In Table 7, we report the percentage of linked External PRs. We find that internal PRs are more likely to be linked with an average of 42.57% per package. This result may not be surprising, as we assume that any core team would be focused on resolving any existing issues in their projects. Interestingly, on average 26.75% of External PRs per package are also linked. This evidence shows that a quarter of External PRs were in response to an existing issue.

*Labels that require attention.* Table 8 shows the frequency count of PRs that might raise developer attention. As expected, the number of these PRs should not be large, as they indicate critical problems for a library. Yet, when looking at the percentages, we deduce that although small, External PRs do have relatively comparative ratios (3.63%) compared to Internal PRs (4.34%) and Bot PRs (1.38%). It is important to note that since labeled PRs account for a small portion of PRs (i.e, 245,693 (78.18%) Bot PRs, 26,797 (9.22%) External PRs and 50,144 (14.73%) Internal PRs), at this stage we cannot make any statistical generalizations. Instead, the evidence shows that External PRs contain PRs that require the attention of developers and might provide fixes to critical issues.

Table 10: Examples of PR content with title and reason for classification.

PR Content	PR title	Reason for classification
Documentation	Update WritingTests.md (onl, 2017c)	The PR modifies the file named 'WritingTests.md'
Feature	feat: Add twitch icon (onl, 2019a)	PR's title includes 'feat' keyword.
Bug	BIG-21501 - EU Cookie warning (Bugfix) (onl, 2016)	PR's title and description contain 'bugfix' keyword.
Refactoring	Major refactoring (onl, 2019b)	PR's title includes 'refactoring' keyword.
GIT related issues	Merging cards theme into master (onl, 2017a)	The PR is for merging another branch to master.
Test cases	Remove TLS account creation tests (onl, 2017b)	PR's description explains about test integration.
Other	Mark the package as having no side effects (onl, 2019c)	The PR modifies a config file (package.json)

In terms of the content of the PRs that require the attention of developers, as shown in Table 9, the top five unique labels for External PR include breaking (78), important (50), urgent (46), on-hold (45) and breaking change (40). Differently Internal PR includes labels such as required (104), change/patch (96), and performance (80), which Bot PR include labels related to security. Interestingly, Bot PRs seem to specialize in fixing security issues, while only having 9.59% of the total unique label keywords. This result is consistent with the intuition that many of the bots detected were dependency management tooling, which may include security vulnerability fixing. Based on these results, we now return to answer the first research question (**RQ1**) *To what extent do External PRs ease maintainer workload by fixing existing issues?*

**Summary for RQ1:** We find that 26.75% of External PRs submitted to a package are linked to an already existing issue. Furthermore, we find evidence that there are External PRs that require the attention of the core team (e.g., referencing breaking changes, urgent, and on-hold labels).

*Most External PR relate to New Features.* Table 10 shows examples of each PR change type, while Figure 5 depicts the frequency count for each type in our sampled dataset. A key finding of our result is that most PRs were related to creating a new feature, which is consistent with the results of Subramanian et al (2022). In terms of types, Bot PRs (380 out of 384 PRs) were the most frequent for bots and also for the category. The most likely reason is that the NPM ecosystem has been popular for using bots to assist with dependency management. Libraries in the ecosystem have been the target of popular bots such as dependabot, greenkeeper, and other dependency management bots. This is confirmed by related work (Rombaut et al, 2022).

*External PR also relate to features, bugs, and documentation, but not refactorings or GIT related issues.* When comparing between the different types of PRs,

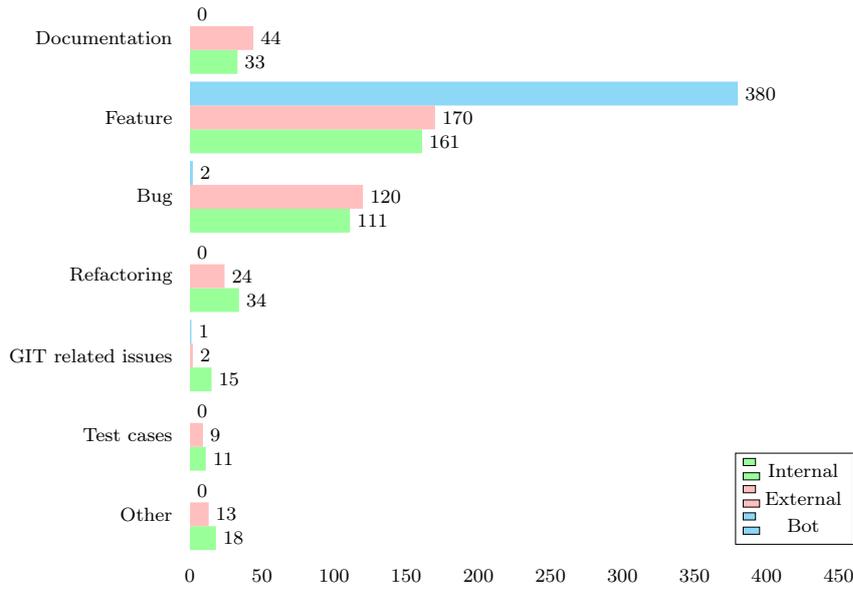


Fig. 5: Frequency count of seven PR types comparing Internal PR, External PR, and Bot PR

we find that External PRs target features (170 PRs), bugs (120 PRs), and documentation (44 PRs). Internal PRs similarly add features (161 PRs), fix bugs (111 PRs), but in addition, have more refactoring-related PRs (34 PRs), and GIT-related issues (15 PRs). We find that statistically, External PR and Internal PR have different PR contents. (i.e.,  $\chi^2 = 14.837$ ,  $p\text{-value} < 0.021$ ). Cramér's V effect size ( $\phi'$ ), indicated a small level of association. We now return to answer the final research question (**RQ2**) *How different are the code changes when comparing External PRs to Internal PRs?*

**Summary for RQ2:** Similar to other PR types (internal and bots), External PRs are most likely to contain changes to add new features (170 out of 384 PRs) to a package. However, unlike Internal and Bot PRs, External PRs tend to focus on documentation (44 out of 384) as opposed to features (380 out of 384) for bots, and refactoring (34 out of 384) for Internal PRs.

#### 4 Lessons Learnt

Returning to the goal of the study, we find that External PRs are almost as important as Internal PRs submitted by members of the core team. Hence,

we make the following recommendations and highlight challenges and future work that this work sparks.

- *Libraries Need External PRs.* Based on the preliminary study, RQ1 and RQ2, we find evidence that the ability of a library to attract and sustain External PRs is crucial. We find that most packages receive External PRs, and an ecosystem contributor is likely to submit External PRs. Thus we show that it is important for library packages to have a constant flow of external contributions. This might be even more important in cases where a library has a single maintainer. Hence, we suggest that libraries consider strategies to attract the community to their library. One interesting avenue for future work would be exploring the motivations for why an external submitter would make a contribution and what factors might attract them to make a contribution.
  - *External PRs attract the attention of maintainers.* RQ1 shows that External PRs can contain changes that attract the attention of the core team. This is good news, as this assistance might provide new ideas or lend a hand to often overworked maintainers. With just over a quarter of External PRs being linked to an already existing issue, this means that these PRs are directly related to actionable and existing problems that can be immediately reviewed and merged into the codebase. Potential research directions would be understanding those External PRs that are not linked. Also, in this study, our evidence only comes from mining the artifacts; the next logical step would be to conduct interview or survey studies to confirm that maintainers see these External PRs as assisting them in maintenance, rather than adding another layer of work for them. Another future research direction would be to explore whether the continued supply of different types of External PRs (RQ2) is a positive factor for the sustainability of a library (to avoid becoming obsolete).
  - *External PRs meet documentation needs.* Results from RQ2 show that External PRs meet needs that are different from Internal PRs, i.e., they are more likely to help with documentation and feature requests. This is especially good news for very active projects such as software libraries that require constant updates to fix bugs and add new features. It is good for maintainers to know that there is a community that helps them manage new features, deprecation, and other critical aspects that need to be communicated back to their users. A potential research direction is to investigate how these documentation needs can be met by automated approaches, to further reduce the workload of maintainers. These results might also indicate that creating an External PR might not require much technical skill or coding experience, as the focus can be on updating the documentation or correcting inconsistencies in its usage.
- On the other hand, we find that External PRs are less likely to submit refactoring changes for a project. This is intuitive, as performing such operations requires more in-depth knowledge of the code.

## 5 Threats to Validity

*Internal validity* - We discuss three internal threats. The first threat is the correctness of the techniques used in the mining and extracting of our datasets. As we use the listed NPM packages and pull request information based on Chinthanet et al (2021), we are confident that our result can be replicated. Furthermore, we contribute a full dataset that can be used by future researchers. The second threat is related to tool selection (e.g., statistical testing). This is because different data sources and tests may lead to different results. To mitigate this threat, we use standard tests such as Spearman’s rank correlation coefficient, Mann-Whitney U test, and Kruskal-Wallis H-test for statistical validation from popular and well-known Python packages (i.e., SciPy Statistical functions<sup>8</sup> (scipy.stats)) The third threat is through our qualitative analysis or manual classification in RQ2. We mitigate these threats by reporting the agreement among three raters using Cohen’s kappa. In this case, all three raters discussed refining the types of PR content until they achieved a high kappa agreement (more than 0.8).

*Construct validity* - Threats to the construct validity of this work are related to the categorizations and assumptions in the study. A threat is the identification of External PRs, which is prone to false positives. Different from prior work by Valiev et al (2018), we define a core contributor as a contributor who has the ability to merge a PR. The bot classification is based on prior approaches by Dey et al (2020) and Golzadeh et al (2020). Furthermore, for RQ1, our identification of keywords is prone to generalization issues. We acknowledge these threats, but are confident as we carefully use empirical standards for systematic classification, with all data available for replication. Finally, we do not take into account the internal activities of maintainers. We believe that this is outside the scope of this work, however, will be considered for future work.

*External validity* - The main threat to external validity exists in the generalizability of our results to other package ecosystems. In this study, we focused solely on the NPM JavaScript ecosystem which has around 2 million packages, with over 180 million downloads in July 2022. However, we have no reason to believe that our analysis is not applicable to other ecosystems that have similar package management systems, e.g., PyPI for Python. Although we analyzed a large number of repositories on GitHub, we cannot generalize our findings to industry or open-source repositories in general. Some open-source repositories are hosted outside of GitHub, e.g., on GitLab or private servers. To mitigate threats to *reliability*, we are careful to state that these recommendations and implications may only be specific to the NPM community, and extension is seen as immediate future work.

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<sup>8</sup> <https://docs.scipy.org/doc/scipy/reference/stats.html>

## 6 Related work

Our work is situated between two research fields. We now introduce and highlight related literature.

***Studies on Third-party Libraries*** Third-party libraries have been studied in various aspects, including third-party library reuse Heinemann et al (2011); Abdalkareem et al (2017); Xu et al (2020), third-party API library Alrubaye et al (2020); Thung (2016), library migration He et al (2021); Cogo et al (2019), Huang et al (2020), and security vulnerabilities in third-party libraries Chinthanet et al (2021); Decan et al (2018). Only a few studies have focused on understanding developer contributions to third-party libraries, which we believe plays an important role in library sustainability. In terms of sustainability of packages, Dey et al (2019) observed that users contribute and demand effort primarily from packages that they depend on directly with only a tiny fraction of contributions and demand going to transitive dependencies, with a case study of NPM packages. Recently, Dey and Mockus (2020) revealed the significant effects of technical and social factors on the developer contribution quality for NPM packages. Although these papers are complementary, to the best of our knowledge, the characteristics of external contributions for third-party libraries have not been studied comprehensively. Differently, **in our work**, we focus on external contributions to third-party libraries, looking at their prevalence and their characteristics.

***Studies On OSS Sustainability*** To sustain OSS projects, previous studies have extensively investigated the motivations and barriers to developers' joining and retention.

*Motivations to make OSS contributions* - The common motivations to make contributions to OSS projects are the joy of programming, the identification with a community, career advancement, and learning Hars and Ou (2001). Additionally, Roberts et al (2006) explored the interrelationships between motivations of OSS developers, revealing that motivations are not always complementary. When comparing motivations between individual developers and companies, Bonaccorsi and Rossi-Lamastra (2006) observed that companies are more motivated by economic and technological reasons. Lee et al (2017) found that the most common motivation of one-time contributors is to fix bugs that affect their work, while the highly mentioned motivation of casual contributors is "scratch their own itch" Pinto et al (2016). **In our work**, although we do not study the motivations for contributing to a library, our study is related to characterizing OSS contributions.

*Barriers to participation in OSS projects* - A study by Fagerholm et al (2014) observed that mentoring increases the chance of developers' active participation. In the pull-based model, a survey by Gousios et al (2016) revealed that the most commonly reported challenge is the lack of responsiveness of project integrators. Steinmacher et al (2013) investigated the first interactions of newcomers in an OSS project. Their results showed that these interactions

affected the onboarding of newcomers. Furthermore, they analyzed pull requests of quasi-contributors and found that non-acceptance demotivated or prevented them from placing another contribution Steinmacher et al (2018). Assavakamhaenghan et al (2021) tried to understand the correlation between the first response given to the first contribution and future contributions. Li et al (2021) observed the significant impacts of pull request abandonment on project sustainability. Complementary, **in our work**, we also analyze pull requests but with a focus on third-party libraries rather than more generic OSS projects.

*Developers' retention and engagement in OSS projects* A study by Zhou and Mockus (2012) found that developers' willingness and participation environment significantly impact the chance of becoming long-term contributors. In addition, Schilling et al (2012) showed that developers' retention in OSS projects is affected by the level of development experience and conversational knowledge. Valiev et al (2018) conducted a mixed-methods study to investigate ecosystem-level factors that affect the sustainability of open-source Python projects. Their results show that projects with more contributors are less likely to become dormant. Iaffaldano et al (2019) conducted interviews with OSS developers to explore what drives them to become temporarily or permanently inactive in a project. The reported reasons were personal (e.g., life events) or project-related (e.g., role change and changes in the project). Recent studies have also focused on understanding what contributions attract newcomers (Subramanian et al, 2022), (Rehman et al, 2020). Meanwhile, the usefulness of automated pull requests, i.e., bots, has attracted interest from researchers in these research areas. Through an empirical study of OSS projects with bots, developers revealed that these bots are useful for maintaining projects (Wessel et al, 2018). Mirhosseini and Parnin (2017) observed that bots can encourage developers to contribute to OSS projects, especially to update dependencies. Alfadel et al (2021) studied Dependabot, a bot used to automatically update vulnerable dependencies. They found that 65% of the created security-related pull requests are accepted. **In our work**, we also observed PRs submitted by bots, finding that bots such as Dependabot are prevalent in Bot PRs.

## 7 Conclusion

This work investigates the extent to which third-party libraries receive support from external contributors (i.e., External PRs) that are not part of the core team. By mining PRs and analyzing them through mixed methods of statistical analysis and qualitative analysis, we show that External PRs are prevalent and just as likely to be accepted as Internal PRs. Our results reinforce the call of core teams that need support. Future work includes research into encouraging and sustaining External PRs, understanding how External PRs could be automated, or could be the focus for newcomers to the ecosystem. We envision that this work can inspire awareness and initiatives to support third-party libraries.

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## Statements and Declarations

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