Understanding and Designing Mechanisms for Attracting and Retaining Open-Source Software Contributors

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Abstract

Open-source software (OSS) is now ubiquitous and indispensable, supporting applications in virtually every domain. Therefore, sustaining this digital infrastructure is of utmost societal importance. One of the significant challenges in OSS sustainability is its low gender diversity. It is a well-known fact that the open-source software community is heavily skewed towards men. A low gender diversity environment is non-inclusive to non-male people. Women are one of the under-represented groups, taking up at most 10% of the OSS population. Several studies have demonstrated that women face more discrimination; for example, in some ecosystems, women have lower code acceptance rates, longer code review delays, and doubts about their skills and abilities. The low diversity and non-inclusive culture can lead to three major challenges. First, it limits the contributor pool, which harms OSS sustainability because OSS projects need a constant supply of effort for development and maintenance. Second, it impedes project success because evidence shows that a higher gender diverse team is more productive and performs better. Third, it affects gender representation and equity, thus preventing all contributors from enjoying the benefits of OSS, such as finding a job.

With much evidence showing the presence of gender discrimination, this dissertation studies why this happens and what might be an effective intervention. The first three studies in this dissertation are mixed-methods empirical studies that aim to explain the low representation of women among other marginalized groups. Because OSS development is a socio-technical activity, I use theories from social sciences and humanities, such as sociology, economics, and linguistics, to derive hypotheses and explain and contextualize results. The first three studies are arranged by the phases of an OSS contributor, with one chapter on each of the phases: newcomer, contributor and long-term contributor, and disengaged.

To conclude the dissertation, I take one step further to develop an intervention to improve the overall diversity and inclusion in OSS. As the curb-cutting phenomenon describes, designs that cater to marginalized groups also benefit a wider range of people. I use insights from the first three studies to inform the design of a dashboard for maintainers to monitor the health of their project community. I tested the dashboard through two rounds of think-aloud studies and one round of longer-term diary studies with OSS maintainers for usability and effectiveness. Overall, maintainers are excited about our dashboard's information and agree that our health indicators are informative and helpful.

Acknowledgements

I wanted to earn a doctoral degree when booking a ticket with a company in the U.K. I saw that, instead of Ms., Miss., or Mrs., Dr. could also be a title. Moreover, it is gender neutral. Dr. also reflects one's intellectual accomplishment. So I decided I wanted a Dr. title. At that time, I did not realize it was a lonely, long, and rugged journey. A journey I could never reach the end without support from all my friends and families! I list them here to pay my gratitude.

First and foremost, I would like to thank my family for their unconditional love. YeYe was strict on my study and homework when I was in elementary school. Although he passed away before I started my Ph.D., I am sure he would be proud of my accomplishment. I am grateful to NaiNai, who started caring for me even before I was born. She had not gone to school for a single day, yet she learned to read on her own. I must have inherited her wisdom and diligence. I am also very grateful to my parents, for they have spent a tremendous amount of time, money, and energy on my education. LaoYe and LaoLao passed away during COVID. I will forever regret that I could not go back to attend their funeral. I also thank GuGu, ShuShu, YiMa, BiaoGe, and BiaoJie for their love and company. Xu Yue helped me with housing and I am looking forward to spending two years with her in Chicago.

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After the outbreak of COVID, I was trapped in the U.S. because flight tickets to China were costly, and flights could be canceled anytime. I was very depressed and suffered from insomnia. I definitely would not have survived without the help of my doctor and therapist.

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When I finally came home this Summer, I developed a new hobby, escape rooms, and I would like to thank all those who played escape rooms with me. They made my thesis writing journey less stressful and more enjoyable. Lei Zhang spent many nights with me after her long work days. Lin Luo, (), and Howard Tang all came a long way to play with me. Kate Cat, Bin Wu, Shuailin Wu, and Candice Wong are also my outstanding teammates.

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Chapter 1

Introduction

Open-source software (OSS) today is ubiquitous and indispensable. As Eghbal's well-known "roads and bridges" analogy [2] suggests, OSS forms our digital infrastructure; just like their physical counterparts, roads, and bridges, OSS is supporting applications in virtually every domain. For example, more than 40% of websites use Apache HTTP Server[1] and its economic value was estimated to be more than 7 billion dollars in the US alone [3]. Therefore, sustaining this digital infrastructure is of utmost societal importance.

One of the biggest challenges in OSS sustainability is its low gender diversity. It is a well-known fact that the open-source software community is heavily skewed towards men [4] (see Section 1.2 for an overview). This low gender diversity environment is found to be non-inclusive to non-male people. As Nafus [5] pointed out that sexist behaviors in OSS are "as constant as it is extreme." Women are one of the under-represented groups, taking up at most 10% of the tech population [6]. Several studies have demonstrated that women are facing more discrimination. Women who are outsiders to a project have a lower pull request acceptance rate when their gender can be inferred from their profile [7]. In addition, Bosu *et al.* [6] found that, in some ecosystems, such as Android, Chromium OS and LibreOffice, women face a lower code acceptance rate and delayed code review feedback. Some female mentors in OSS reported that their skills and abilities are underestimated; for example, some newcomers do not take their advice/feedback as seriously as those from male mentors [8]. Some female contributors reported that they face "a harsh onboarding experience or OSS environment" [8], including acrimonious talk [5]. Some stated that they have to "prove themselves by working extra hard" [8]. The low diversity and non-inclusive culture can lead to three major challenges: limits pool, harms project success, and negatively affects representation and equity.

First, a non-inclusive environment limits the available contributor pool. A constant supply of effort is essential to OSS projects' sustainability because OSS projects need contributors for fixing bugs, adding new features, and adapting to evolving technical and non-technical environments and requirements. When projects lack appropriate levels of contributor effort, they are at risk of being undermaintained [2, 9, 10], which can cause serious problems. For example, both OpenSSL and Bash are widely used OSS but were maintained by a single developer for a long time. These two libraries had security bugs, *e.g.*, the "Heartbleed" bug[2]

[1] https://w3techs.com/technologies/history_overview/web_server

[2] https://www.digitaltrends.com/computing/heres-a-list-of-websites-allegedly-affected-by-the-heartbleed-bug/

in OpenSSL could allow hackers to capture secure information being passed to vulnerable web servers, and the "Shellshock" bug in Bash could allow unauthorized access to a computer system that went unnoticed or unfixed for many years.

Second, low gender diversity can harm project success. High gender diversity is found to be associated with better performance. A software team consisting of mostly white male programmers is generally not a good representation of their intended users because software is rarely designed for a single demographic subgroup. However, this is often neglected because OSS developers often have less concern over who their users are [5]. In software engineering, a recent study [11] confirmed that mixed-gender software engineering teams are associated with better performance because men and women tend to display different personalities, and more successful teams can leverage positive personality traits that are associated with better team performance [12].

Third, it negatively affects representation and equity. Prior studies have shown that a male-dominated environment is associated with discrimination against minority groups [5]. Discrimination towards women in male-dominated fields can cause the "imposter syndrome" effect: women tend to consider themselves disqualified or frauds despite being knowledgeable. Such effects can lead to anxiety, depression, lowered self-esteem, and self-handicapping behaviors [13].

Furthermore, a non-inclusive culture hinders marginalized groups' personal development. More than half of the respondents to a GitHub survey noted that their OSS experience helped them get their current job and build their professional reputation [14]. A non-inclusive culture that discourages marginalized groups obstructs them from gaining these opportunities.

However, this dissertation does not limit the scope to solving problems specific to only marginalized groups. The "curb-cutting" effect [15, 16] describes a phenomenon that designs that benefit marginalized groups, such as curb-cuts for people with disabilities, also allow people to push baby carriages, shopping carts, luggage on wheels, bicycles, *etc.*. This dissertation uses the problem of low gender diversity as a starting point to find methods to include overall diversity and inclusion in OSS. With higher diversity and inclusion, it will be easier for OSS projects to attract a wide variety of contributors and retain them, thus improving projects' sustainability.

While there has been a long string of scholarship on OSS participation, relatively little is known about why there is a lack of diversity and inclusion, what attributes to marginalized groups' long-term engagement or premature disengagement, and, most importantly, what can be some effective interventions. In this dissertation, I divide an open-source contributor's career trajectory into roughly three phases (illustrated in Figure 1.1): newcomer, contributor and long-term contributor, and disengaged. These phases roughly follow the onion model [17, 18], which describes OSS teams as a core-peripheral structure.

In the next two sections, I present prior studies on different phases of open-source contributors and statistics of gender distributions in OSS.

1.1 Literature review on OSS contributors

There is a rich body of literature on OSS participation. In this section, I group related studies into different phases of a typical OSS contributor's career trajectory.

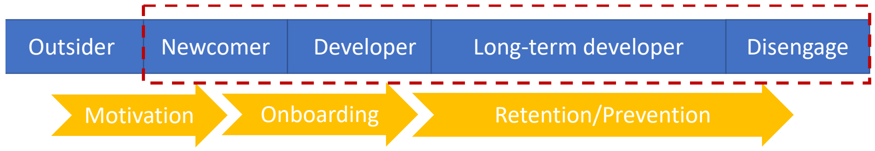


Figure 1.1: An open-source contributor's different phases. Phases bounded by the red rectangle are studied in this dissertation.

Many prior studies use the *onion model* [19, 17, 20] to describe an OSS project's structure - core contributors who contribute most of the code and manage the projects and peripheral contributors who make a smaller portion of contributions. In this dissertation, I do not distinguish between core and peripheral contributors. My primary concerns are attracting and retaining contributors. It is very likely, however, that a long-term contributor becomes a core contributor to one of the OSS projects.

1.1.1 From an outsider to a newcomer

Studies revealed that there are intrinsic, *e.g.*, having fun, and extrinsic motivations, *e.g.*, better jobs, and career advancement, to join OSS [21, 22, 23]. A recent study showed that more contributors are driven by intrinsic motivations and newcomers use their OSS experience as their portfolio in job hunting [24]. The literature found that women's motivations to use technology relate to accomplishments while men's motivations are more related to their enjoyment of technology [25]. Balali *et al.* [8] argued that the difference in motivations might explain why some women's disengagement.

1.1.2 From a newcomer to a contributor

There are studies on what makes an OSS project attractive to contributors. On social coding platform, *e.g.*,GitHub, users can make inferences of a project's characteristics based on signals, *i.e.*, visible features, and cues on the user interface [26]. For example, Trockman *et al.* [27] showed that certain signals on social coding platforms could allow users to infer the quality of a project. Santos *et al.* [28] found that license restrictiveness and their available resources influence a project's attractiveness. Knowing that different genders have different problem-solving styles [29], one important yet unanswered question is how contributors of different genders value different aspects of a project.

There is a large body of work on identifying the barriers contributors face when making their initial contributions. For example, Steinmacher *et al.* [30, 31] identified 58 barriers that may hinder OSS newcomer's onboarding experience. Some of the barriers are finding a task to start with, lack of domain expertise, not receiving an answer, code comments not being clear.

Some of the barriers are related to differences between genders. Using the GenderMag kit, Padala *et al.* [32] found that the tool for OSS is gender-biased, and women in general face more barriers than men. Moreover, in Balali *et al.*'s work [8], they listed out additional challenges that female newcomers need to face, including their low self-efficacy.

A natural follow-up study is to explore what type of projects is more friendly to marginalized groups. Foundjem *et al.* [33] found a significant correlation between high gender diversity (65% for both females and non-binary contributors) and increased patch acceptance rates (13.5%).

However, before a newcomer onboards an OSS project, one needs to identify a project to make a contribution to. Relatively little is known about how newcomers can find a friendly project. There exist many websites that try to help first-time OSS contributors find a suitable project. Some of these websites curate a list of tutorials for newcomers, [3] [4] some have a checklist to evaluate a project's fitness, [5] and some collect projects that want help.[6] Nevertheless, with such resources available, Tan *et al.* [34] found that many contributors still fail to make a contribution. Our work contributes to this gap of knowledge and explores signals that can help newcomers find a suitable OSS project.

1.1.3 From a contributor to a long-term contributor

Some studies found evidence against some bias allegations. Although women are believed to be stuck with non-code tasks, a 2013 study on FOSS survey showed that 76% of the female contributors contribute code [35]. El Asri *et al.* [36] found that female contributors, in fact, are as productive as their male counterparts. Their career trajectory follows relatively the same pattern as male contributors and remains more involved in projects.

Nevertheless, subtle bias and discrimination are still present. For example, Terrell *et al.* [7] found pull requests (PRs) from women who are not part of the project are less likely to be accepted than their male counterparts, but when gender is not visible, women have a higher PR acceptance rate. Wang *et al.* [37] pointed out that a bigger confidence-competence gap, *i.e.*, low self-efficacy despite technical brilliancy, is an additional threat women are facing in their OSS journey. Vedres *et al.* [38] found that it is not the female gender category, but rather the female behavioral pattern, *e.g.*, having more women contributors as collaborators, that put women in disadvantages; men following a similar pattern also face disadvantages.

A 2019 survey for FLOSS contributors [39] found that people's attitude towards female contributors has improved, but there are people who have strong opinions against the study of gender in OSS. More importantly, this survey [39] reported that more than one-third of the female survey participants faced sexism, such as offensive comments or insinuations on women's incompetence, and one-fifth of them felt that their code is harder to get accepted. However, Imtiaz *et al.* [40] conducted a quantitative study on GitHub using Williams and Dempsey's gender bias framework but found that most of the gender bias effects, such as tight-rope and prove-it-again, are invisible.

While these studies identified the presence of bias and discrimination, still more work has to be done to study how to improve marginalized groups' sustained participation. The studies mentioned above focused on individual behaviors. This dissertation analyzes sustained participation from the perspective of contributors' social connections on GitHub.

[3] https://www.firsttimersonly.com/

[4] `https://github.com/freeCodeCamp/how-to-contribute-to-open-source`

[5] https://opensource.guide/how-to-contribute/

[6] https://up-for-grabs.net/

1.1.4 Disengage from OSS

A recent study by Iaffaldano *et al.* [41] provides an overview of why OSS contributors take a break or eventually withdraw from the community. Some of the personal reasons include other professional or life event priorities, which are also found by Miller *et al.* [42] and loss of interest in the project. Project related reasons include changes in projects or the lack of communication. In addition, some contributors mentioned that the social behavior of the community can also drive people away. Being reactive may help newcomers feel welcomed whereas ignoring contributions may drive contributors away.

Literature also found that stress and burnout can be a reason for disengagement from OSS, as evident in many blog posts, talks, or podcasts [43, 44, 45] In addition to a high volume of requests [44], unfriendly or even aggressive tones are also a source of burnout [46], making projects hard to attract and retain contributors.

Negative interaction, such as pushback in code review [47] and toxic language [46, 5] can demotivate and burn out developers. Egelman *et al.* [47] found that, in a corporate setting, reviewers blocking code changes during code reviews can be a source of negative experience. Prior works have explored how to automatically detect negative experiences, such as pushback behaviors with logs-based metrics [47] and toxicity with linguistic features [46]. This dissertation further investigates how to automatically detect negative interactions among OSS contributors.

More specifically, plenty of studies focus on reasons behind disengagement of marginalized groups, such as women or newcomers. Research shows that women developers are generally more likely to leave the project than men [48]. Women face more barriers in OSS [8, 49], such as unwelcoming language [50], unsolicited sexual advances [50], gender bias in tool design [32], distrust in their competence as a mentor [8], lower code acceptance rate [7, 6], or the lack of inclusion for a female leader [6]. Scholars also pointed out that solutions to support women's sustained participation may be different from that of men [51, 52].

1.2 Literature review on OSS gender distribution

As the problem of low gender diversity is gaining more attention, many studies have tried to estimate the gender composition in the OSS community. Although all reports on a low percentage of women contributors, these numbers range from 1% to 12%. Many reasons can cause dissimilarity among the data, such as the data collection methods, time, sampled populations, and sample size. In this section, we group prior works that reported gender distribution in data collection methods: survey *vs.* data mining. Each method has its merits and shortcomings. For each method, we order the studies by the time they collected the data. Note that since these data were collected in different sub-populations and with varying sample sizes, the chronological ordering does not imply any longitudinal trend. Finally, we list studies that reported gender ratios in specific projects or ecosystems.

1.2.1 Surveys

Table 1.1 lists the studies that rely on survey data to calculate gender distribution. Surveys can capture people's self-identified gender and arguably increase the precision of gender

Table 1.1: Women ratios reported from survey data.

Year	Source	Sample size	%	Citation
2001	Online survey	5,478	0%	Robles *et al.* [53]
2002	Online survey	2,784	1.1%	Ghosh [54]
2001∼2002	Email	684	2.5%	Lakhani *et al.* [22]
2002	Email	79	5%	Hars and Ou [55]
2003	Online Survey	1,588	1.6%	David *et al.* [56]
2013	Online survey	2,183	10.35%	Robles *et al.* [57]
2015	Online survey	816	24%	Vasilescu *et al.* [58]
2017	Online survey	6,000	5%	GitHub [50]
2017	Online survey	64,000	7.6%	StackOverflow [59]
2019	Online survey	119	10.9%	Lee *et al.* [39]
2021	Online survey	242	7.6%	Gerosa *et al.* [24]

Table 1.2: Women ratios reported from mining data.

Year	Source	Sample size	%	Citation
2012	Email subs + US Census	1,931	8.27%	Kuechler *et al.* [62]
2012	StackOverflow	2,588	11.24%	Vasilescu *et al.* [63]
2015	GitHub + genderComputer	1,049,345	8.71%	Kofink [64]
2015	GitHub + genderComputer	873,392	9%	Vasilescu *et al.* [65]
2017	GitHub + self-report on social media	328,988	6.36%	Terrell *et al.* [7]
2017	OpenStack + genderize.io	-	10.4%	Izquierdo *et al.* [4]
2019	GitHub + Namsor	300,000	9.7%	Qiu *et al.* [48]
2019	Gerrit + genderComputer based on social media profile	4,543	8.8%	Bosu and Sultana [6]
2020	GitHub + genderComputer+Namsor	1,954 core	5.35%	Canedo [66]
2021	GitHub + genderComputer+Simple Gender[67]	1,634,373	5.49%	Vasarhelyi *et al.* [68]
2021	GitHub + genderize.io	65,132	10%	Prana *et al.* [69]
2022	Software Heritage + Gender Guesser	21.4M	10%	Rossi *et al.* [70]

identification [60]. Surveys targeting a specific population can provide in-depth and more accurate insights. However, survey data, albeit highly reliable and accurate, are prone to selection bias. People who responded to the survey may be qualitatively different from those who did not respond because of differences in survey accessibility and individual motivation [61]. Moreover, survey datasets are usually small, making it hard to obtain generalizable results.

1.2.2 Mining trace data

Table 1.2 shows the studies that rely on mining data to report gender distribution. Gender inference based on mined user information provides a more representative, large-scaled sample,

Table 1.3: Women ratios in different ecosystems or open-source projects.

Year	Source	Ecosystem(s)	Sample size	%	Citation
2014	Mailing list	Drupal	3,342	9.81%	Vasilescu *et al.* [73]
2014	Mailing list	Wordpress	3,611	7.81%	Vasilescu *et al.* [73]
2016	Online survey	Apache	765	5.2%	Sharan [74]
2005-2016	GitHub	Linux	14,905	8%	Cortázar [75]
2016	Online survey	Debian	1,479	2%	Raissi *et al.* [76]
2019	GitHub + Namsor	Angular.js	1,601	3.4%	Asri and Kerzazi [77]
2019	GitHub + Namsor	Moby	1,824	3.5%	Asri and Kerzazi [77]
2019	GitHub + Namsor	Rails	3,723	4.2%	Asri and Kerzazi [77]
2019	GitHub + Namsor	Django	1,672	5.3%	Asri and Kerzazi [77]
2019	GitHub + Namsor	Elasticsearch	1,127	4.2%	Asri and Kerzazi [77]
2019	GitHub + Namsor	TensorFlow	1,735	5.8%	Asri and Kerzazi [77]
2019	Gerrit + genderComputer	Android	258 core	3.87%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Chromium OS	151 core	3.97%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Couchbase	24 core	4.17%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Go	90 core	7.77%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	LibreOffice	68 core	1.47%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	OmapZoom	60 core	10%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	oVirt	34 core	2.94%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Qt	159 core	3.12%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Typo3	73 core	4.1%	Bosu and Sultana [6]
2019	Gerrit + genderComputer	Whamcloud	19 core	0%	Bosu and Sultana [6]
2021	Online survey	Linux	2,350	14%	Carter *et al.* [78]

and it also avoids the burden of the survey respondents and the efforts taken to collect survey results.

However, researchers often need to infer gender because not all platforms collect users' gender, and not all users disclose their genders online. From the studies, we summarize two primary information sources for gender inference: names and information from other social media platforms. Commonly used name-based gender inference tools include Namsor [71], genderComputer [63], GENDER GUESSER,[7] and genderize.io.[8] See Sebo [72] on a comprehensive comparison among these tools. The most significant shortcomings of these computational tools are non-perfect accuracy and the assumption of binary gender. Some studies cross-link a user's account to other social media platforms, such as LinkedIn, Facebook, Google search, and the now deprecated Google plus. This method can capture users' self-reported gender.

1.2.3 Ecosystems

Table 1.3 lists studies that report gender ratios in specific software ecosystems. Many of these studies focus on specific projects rather than the entire ecosystem. In addition to these

[7]https://pypi.org/project/gender-guesser/
[8]http://www.genderize.io

quantitative figures, some studies also provide comparisons across ecosystems. For example, women are more represented in COBOL legacy systems than in new systems using Java or C++ [79]. Women are also more likely to be found in Ruby but not in pure backend or PHP-focused frontend communities [68]. However, to the best of our knowledge, there is not a study that covers all major ecosystems.

1.3 Thesis

In this dissertation, I conduct a series of empirical studies using a mixed-methods approach to gain a better understanding of factors that influence diversity and inclusion in OSS. Because software development is a collaborative, human-centric activity, I use social science theories to inform study design, derive hypotheses, and explain and contextualize results. The abundant trace data from online coding platforms, *e.g.*,GitHub, allows us to perform large-scale data analyses to answer research questions empirically. I employ quantitative and qualitative methods in my research because they complement each other and allow me to get different perspectives on the research question. I use quantitative methods, such as sophisticated statistical analyses and advanced machine learning models, to discover patterns from large-scale, longitudinal data. I use qualitative methods, such as surveys and interviews, to validate our computational operationalizations and gain insight from real contributors.

While there are studies showing the presence of discrimination, relatively little is known about why this happens and what might be a useful/effective intervention. This dissertation includes a series of mixed-methods empirical studies that aim to explain the low representation of women among other minority groups. Because OSS development is a socio-technical activity, I use theories from social sciences and humanities, including social capital theory, signaling theory, and linguistics politeness theory, to derive hypotheses and explain and contextualize results. Using the results from these studies as a foundation, this dissertation also takes one step further to designing and prototyping/testing/piloting interventions.

1.3.1 Thesis statement

Here is my thesis statement:

Social science theories driving computational methods on big data explain the mechanisms behind open-source contributors' sustained participation as well as help us design interventions to improve open source community health.

Note: In this dissertation, I use "we" when describing works that I collaborated with other researchers.

1.3.2 GitHub as the research context

This dissertation uses GitHub, one of the most widely used social coding platforms, as the research context. I chose GitHub for several reasons. First, GitHub is the most widely used online social coding platform, with more than 56M users as of September 2020.[9] Second, GitHub has a rich set of features, *i.e.*, visible cues, to reflect contributors' social dynamics. For

[9]https://octoverse.github.com/

example, there is the number of daily commits [80] as a signal of a contributor's commitment and competence, or the number of stars [81] for a repository to reflect its popularity. Users can put up signals, such as badges in the README [27] or a CODE OF CONDUCT [82], to demonstrate their project's level of maintenance. These features can serve as signals that can help contributors make informed decisions [26].

The abundance of signals leads to many interesting research questions. For example, the presence of a daily activity streak may affect how contributors behave [80]. Social signals, such as users' names or profile pictures, may influence how their PRs are treated [7, 83].

Finally, all actions on GitHub leave traces and are available for everyone. Therefore, we are able to use this information to conduct analyses on their social networks, contribution patterns, code quality, *etc.* The trace data and signals are available and easy to manipulate with MySQL and MongoDB [84]. This makes many empirical analyses possible.

1.3.3 A note on the use of binary gender

Although gender, a socially constructed concept, is non-binary, it is sometimes not impractical to include non-binary gender in a computational model. Throughout this dissertation, I use GitHub trace data, which does not record participants' gender. Therefore, we often need to infer gender based on information we can observe, usually names, photos, and information from other social media platforms, *e.g.*, Google+ and LinkedIn.

However, all these methods have their limitations. Commonly used gender inference tools using names or photos often assume binary gender, and the accuracy is not perfect [72]. Even though we can sometimes find users' self-reported gender from their profiles on other websites, the number of users with whom we can link their accounts is relatively small. As a result, to obtain a large dataset of contributors with their gender, the best method we can rely on is the name-based inference tools.

Despite these limitations, I argue that conducting gender analysis with imperfect gender inference is necessary and imperative. While the severe underrepresentation of women and other marginalized groups is widely recognized in OSS, much more work is needed to understand the reasons behind the low diversity. Moreover, we have little empirical evidence on how the situation has changed over time and in different sub-communities and ecosystems.

Though imperfect, a large dataset of OSS contributors with inferred gender allows us to observe the approximate gender distribution at different times and in different ecosystems [70]. These observations can provide us feedback on the effectiveness of our efforts to improve gender diversity in OSS. They can also point us to the most and the least diverse communities to conduct future studies. With access to large datasets with inferred gender, we can also build statistical models to test hypotheses developed from social sciences theories on gender differences (Chapter 3). Moreover, since women contributors are rare in open-source, using inferred gender, we can preselect a small group of people whose likely to be women and then manually verify their genders.

Therefore, because obtaining a large dataset of accurate self-reported gender, including non-binary options, is impractical and almost infeasible, in some places, I use binary gender as a simplification to make the analyses tractable. When possible, however, such as when inviting participants for interviews or surveys, I only use computationally inferred gender as a rough approximation to help me find non-men contributors. I use their self-reported gender in the analyses and reports. Overall, I only use automatic name-based gender inference to capture gender distribution and perform analyses at the population level. As a result, my studies' results should be considered approximations of the actual gender distributions in the OSS community.

1.3.4 Dissertation outline

This dissertation presents a series of empirical studies that focus on different phases of an OSS contributor.

Chapter 2: Help Contributors Choose Projects

While prior works have extensively studied contributors' onboarding experience, this chapter focuses on the earlier and relatively less studied stage in the onboarding process: how *newcomers* choose which projects to contribute to. This work is based on signaling theory, a framework borrowed from economics [85, 86] and biology [87]. The signaling theory states how one may use visible cues to infer a person or an item's hidden properties. This is relevant to OSS social coding platforms as Dabbish *et al.* [26] showed that contributors make inferences on projects based on signals. To better guide new contributors to find a suitable project, we interviewed contributors with various degrees of experience for their insight on how to use signals on GitHub to infer how inclusive and newcomer-friendly a project is. From the interviews, we identified helpful signals and built a model to test if they are significantly associated with bringing in newcomers. This chapter consists of the following conference paper:

[88] H. S. Qiu, Y. L. Li, S. Padala, A. Sarma, and B. Vasilescu, "The signals that potential contributors look for when choosing open-source projects," Proceedings of the ACM on Human-Computer Interaction, vol. 3, no. CSCW, pp. 1–29, 2019.

Chapter 3: Sustained Participation

This chapter concerns contributors and long-term contributors. Although contributors' sustained participation has attracted much attention, little is known about the gender difference. Applying survival analysis, we found that women contributors leave GitHub earlier than their male counterparts. In other words, women contributors have shorter career spans on GitHub. Software development is collaborative; therefore, this chapter studies contributors' sustained participation using social network theories. Social capital theory, a theory explaining resources one can gain from their network connections, provides insight into how contributors' network connections can affect their sustained participation and why there is a difference between genders. We used the social capital theory to identify network structures associated with contributors' prolonged participation. We used a survival analysis model and surveys to triangulate our results. The results reveal possible signals on social coding platforms to support women in developing social capital. This chapter consists of the following conference paper:

[48] H. S. Qiu, A. Nolte, A. Brown, A. Serebrenik, and B. Vasilescu, "Going farther together: The impact of social capital on sustained participation in open source," in 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE). IEEE, 2019, pp. 688–699.

Chapter 4: Detecting Interpersonal Conflicts

This chapter presents our study on disengagement prevention: we study how to detect interpersonal conflicts in issue discussions and code reviews automatically. Our work builds on two prior studies. Egelman *et al.* [47] introduced the concept of *pushback* to refer to the perception of unnecessary interpersonal conflict in code review and presented a classifier using meta-information in Google's code review, *e.g.*, number of comments, reviewing time. Around the same time, Raman *et al.* [46] proposed to use linguistic features to detect *toxicity*, *i.e.*, rude, disrespectful comments in GitHub issue conversations. The two concepts, *i.e.*, pushback and toxicity, are distinct yet similar. We conducted a systematic evaluation of the two complementary methods, *i.e.*, meta-information and linguistic features, on detecting the two concepts, in both corporate (Google) and open-source (GitHub) settings and both types of conversations (issue and code review). The evaluation also allowed us to identify signals that can flag potential interpersonal conflicts in open-source development. This chapter consists of the following conference paper:

[89] H. S. Qiu, B. Vasilescu, C. Kästner, C. Egelman, C. Jaspan, and E. Murphy-Hill, "Detecting interpersonal conflict in issues and code review: Cross pollinating open-and closed-source approaches," in 2022 IEEE/ACM 44th International Conference on Software Engineering: Software Engineering in Society (ICSE-SEIS). IEEE, 2022, pp. 41–55.

Chapter 5: Intervention: A Dashboard for Maintainers

This chapter presents an intervention we built: a dashboard for open-source maintainers to monitor health indicators that are found to impact diversity and inclusion by prior research. We identified health indicators from the literature, studies presented in previous chapters, and interviews with maintainers. Our dashboard focuses on the indicators that are important but not currently readily visible on social coding platforms such as GitHub. Among others, our dashboard included indicators of pushback in code review, tone of issues and pull request discussions, and social capital measures. In addition to summaries of these indicators, we provided coaching on what possible management actions maintainers can take to improve the health of their project. We also included a gamification function that compares the focal project with similar projects to give maintainers a reference on how well they are doing.

We iterated and refined our design through two rounds of think-aloud studies with open-source maintainers. We then tested the usability and effectiveness of this intervention via a two-week dairy study with open-source maintainers. Through our user studies, we found that maintainers were generally excited about the information that our dashboard provides and agreed that our health indicators are informative and helpful.

Chapter 6: Conclusion

I conclude this dissertation with a reflection on its contribution and discussions. I also list some potential future work that I plan to explore after graduation.

Chapter 2

Help Contributors Choose Projects

While prior work has extensively studied the motivations of open-source contributors in general, relatively little is known about how people choose which project to contribute to, beyond personal interest. This question is especially relevant in transparent, social coding environments like GitHub, where visible cues on personal profile and repository pages, known as signals, are known to impact impression formation and decision making. In this chapter, we report on a mixed-methods empirical study of the signals that influence contributors' decision of joining in a GitHub project. We first interviewed 15 GitHub contributors about their project evaluation process and identified important signals they used, including the structure of README and the amount of recent activities. Then, we proceeded quantitatively to test out the impact of each signal based on the data of 9,977 GitHub projects. We reveal that many important pieces of information lack easily observable signals, and that some signals may be both attractive and unattractive. Our findings have direct implications for open-source maintainers and the design of social coding environments, e.g.*, features to be added to facilitate better project searching experience.*

2.1 Introduction

Open-source software infrastructure is ubiquitous, powering applications in virtually every domain [2]. Yet, despite their importance, many open-source projects lack appropriate levels of contributor effort and are thus at risk of being undermaintained [2, 9, 10]. In projects with only one or two core contributors, of which there are many [90], lack of time or interest of the main contributors poses serious sustainability risks [9, 91, 41]. Recruiting new contributors can, therefore, help ensure the sustainability of open-source projects.

Many researchers have studied why skilled workers contribute to open-source. Prior work found that starting to contribute to, and remaining engaged with open-source is influenced by a mixture of intrinsic and extrinsic factors [92], among which identifying with the community, feeling obligated to contribute back, learning opportunities, personal needs, and signaling one's skills to potential employers are all important [93, 22, 94, 95].

What is less known, however, is how people decide to contribute to particular projects *based on partial information about the projects*. This is especially relevant to contributors who are working on an open-source project for fun or to gain experience. Since these people may

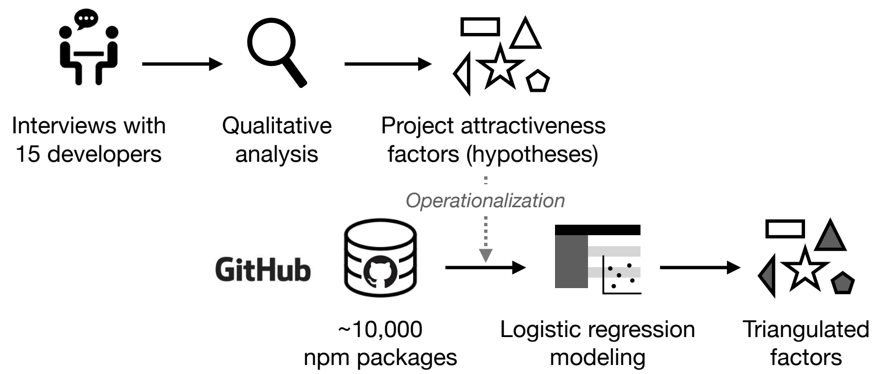


Figure 2.1: Overview of our study design.

choose from many open-source projects, it is helpful to compile a set of generally applicable rules to guide contributors in selecting a better project.

We are able to answer this question because, compared to their predecessors, social coding platforms like GitHub, Bitbucket, and GitLab offer a high level of *transparency*, achieved by displaying a multitude of visible cues (or *signals* [96]) on individual and project public profile pages [26, 97]. For example, on GitHub—the most popular open-source hosting platform—there are signals of individual popularity, such as a user's number of followers, and signals of project activity, *e.g.*, the number of contributors and issues, among many others. As prior studies show, this high level of transparency enables people to make rich inferences about each other's technical expertise and level of commitment [26, 97]. Similarly, to inform their decision whether to join a project, in many cases potential contributors must rely on partial information derived from signals available online. It is therefore important to study how people infer the characteristics and qualities of an open-source project based on the cues they can observe, and how these signals influence their decision to contribute to the project.

In this paper, we build on the literature on transparency in social coding environments to empirically explore a new question:

RQ$_1$. *How do people use signals, if at all, when choosing an open-source GitHub project to contribute to?*

Our study uses a mixed-methods design (Figure 2.1). We start qualitatively by interviewing 15 GitHub users, sampled to represent a diversity of experience contributing to open-source, gender, and geographic, cultural, and technical background. From these interviews, we identify which signals are perceived as most influential when evaluating open-source GitHub projects for potential contribution. Then, we proceed quantitatively by mining trace data from 9,977 open-source GitHub projects (stratified by number of stars) and testing hypotheses, using multiple regression modeling, about the impact of the different signals on attracting new project contributors.

Our results reveal several key signals used to inform the decision whether or not to contribute to a GitHub project: i) a README file with thorough contents and clear structure, describing what the project does, how to get started using it, what a new contributor could work on, and what guidelines they should follow; ii) the availability of scaffolding, such as issue and pull request templates, or issue labels; iii) how actively maintained the project is, along multiple dimensions, such as the number of contributors and the recency of commits; iv) the friendliness of the maintainers in issue and pull request discussions; and v) project popularity. Moreover, we find that some signals can be considered both attractive and unattractive by different users. For example, from the interviews, we found that, while typically positive, the presence of detailed contributing guidelines is also seen by some contributors as "off-putting", as it can set a higher bar to participation and impose too much process overhead. Also, some signals are important in the decision process but may be unclear to first-time GitHub contributors. For example, our model shows that politeness is an important signal for arbitrary new contributors but not for first-time GitHub contributors.

Our results have direct implications for multiple stakeholders. First, we provide open-source project maintainers with actionable insights that can help make their projects more attractive to external contributors. Second, we uncover several cues that potential contributors look for in a project, such as the responsiveness of the project maintainers and the friendliness of the community discussions, that are currently not readily observable in the GitHub UI; our participants browsed through multiple pull request and issue threads to make qualitative inferences about these properties. These insights can help tool builders and designers of collaboration platforms like GitHub develop new signals, *e.g.*, in the form of badges [27], to make these properties more salient.

In the next sections, we frame our discussion in the context of signaling theory, consider related research, describe our methodology, present the results of our interviews and data modeling, and finally discuss implications of our findings.

2.2 Related Work

The process of attracting and onboarding contributors to open-source projects has a long history of scholarship; for an overview see, *e.g.*, Crowston *et al.* [98]. The process consists of multiple stages. Starting from an intention to contribute to open-source, one should ① *discover a relevant project*, ② *find an opportunity to contribute*, then ③ *make a first contribution* (*e.g.*, submit an issue report or a pull request). Then, by continuing to make contributions and ④ *demonstrate commitment* to the project over time, one can ⑤ *be recognized as a core contributor* or maintainer. As turnover is natural in open-source, eventually some contributors will ⑥ *disengage*.

2.2.1 Knowledge gap: How people choose which projects to contribute to

There is a rich body of literature (*e.g.*, [99, 100, 101, 102, 103]) on what happens to open-source contributors *after they identify a project* they intend to contribute to (stages ②—⑥), in terms of their onboarding into the project core team and their long-term participation and turnover. In particular, Steinmacher *et al.* [31, 104, 105] reported, in a series of studies, on how the onboarding process can be long and demotivating for newcomers, who face various social and technical challenges when trying to *find a first task* they can complete and adapt to the project's contribution standards, culture, and norms. The authors identified

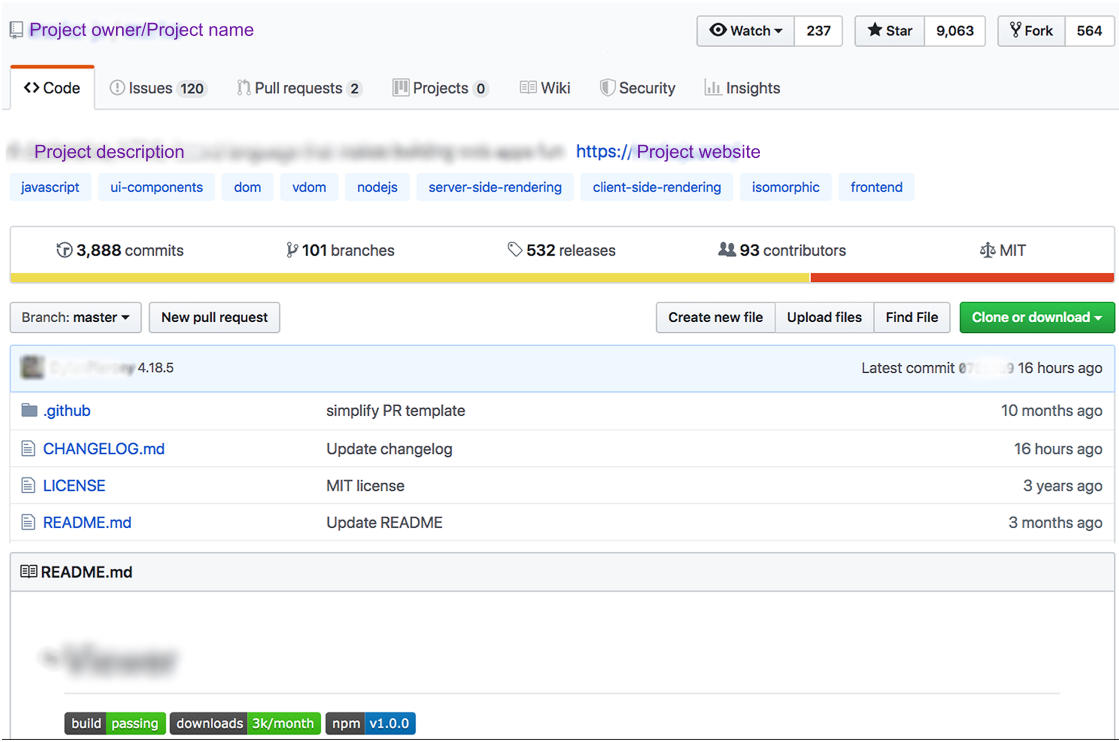


Figure 2.2: A snapshot of a GitHub project page (anonymized).

19 reasons that a new contributor's pull request was rejected, both social and technical, including receiving impolite answers from maintainers, the pull requests being duplicated, not needed, or mismatched with the maintainers' vision, lack of tests, not following guidelines, and not receiving an answer at all; these latter barriers have also been reported in other online collaboration contexts outside open-source, especially Wikipedia [106].

In contrast, we focus on the earlier and relatively less studied stage in the onboarding process: *how people choose which projects to contribute to* (stage 1). Two forces can influence this decision [107]: individual motivation and project attractiveness. Individual motivations are generally well understood, and can be both intrinsic, *e.g.*, personal need for that software or feeling obligated to contribute back, and extrinsic, *e.g.*, career advancement [22]. However, what project actions and characteristics influence project attractiveness to outsiders is still an open question [108].

Studying what makes projects attractive is especially important because, as opposed to individual motivation which is typically inherent to the potential contributors, project attractiveness can be to a larger extent controlled by the project maintainers, as we will argue in the remainder of this paper. Therefore, increasing project attractiveness has the potential not only to reduce some onboarding barriers, but also to improve the sustainability of open-source projects.

2.2.2 Signaling and transparency in online coding environments

On transparent, social coding environments like GitHub, the question of how people choose projects is especially relevant, as a wealth of signals (visible cues indicating otherwise less readily observable qualities [109]) about an open-source project's history of activity and contributors is available on the project's homepage, *e.g.*, the number of commits, contributors, forks, issues, pull requests, star gazers, and watchers. In addition, GitHub renders a project's README.md file as part of the project's homepage. This file gives maintainers a chance to further customize their project's signals, either through free text, *e.g.*, contributing guidelines and documentation on how to install the software, or through badges [27] embedded into a project's README; badges such as build passing and PRs welcome are customizable images that typically reflect the status of different online services the project is using, *e.g.*, continuous integration testing, or expressions of intent, *e.g.*, soliciting pull request contributions. An example of a typical GitHub project page is shown in Figure 2.2. Finally, the transparency provided by individual "profile pages" on GitHub, which aggregates personal information and information about one's history of contributions to open-source projects on GitHub, enables inferences about the contributors' expertise and level of commitment [97, 110], and even makes salient their demographics [111, 58].

Signaling theory, going back almost half a century in economics [85, 86] and biology [87] (see Kirmani & Rao [112] for an overview), provides a framework for reasoning about how these visible cues might impact project attractiveness in open-source. Signaling theory has also been widely applied to social computing systems, to understand how people make inferences using online profile data in contexts as diverse as social networking sites [96, 113, 114], fashion [115], peer-to-peer lending markets [116] and rentals [117], and peer production [97].

In general, signaling theory is applied in scenarios where selections are made under information asymmetry. These are decision making situations typically involving two parties, a signaler, with access to all the information, and a receiver, who is less informed, in which the former would be selected by the latter based on the information carried by the signal. Across all such selection scenarios, an important attribute of signals is their *visibility*: receivers tend to prefer signals that are easier to observe and to interpret over those that are costlier to assess, even when the former are less reliable [118]. Another important attribute of signals is their *production cost*: signals that are costlier to produce, therefore harder to fake, are considered more reliable [119]. For example, in biology, the peacock's heavy tail feathers are both visible and costly to maintain, as they are a highly observable ornament which makes the animal more vulnerable to predators. Therefore, the peacock's tail feathers signal the bird's quality [87]: having survived despite this handicap, the peacock is perceived by potential mates as more attractive and more fit [120]. In economics, a similar signal is holding a degree from a reputable institution: the job seeker's ability, which is otherwise less visible, is being communicated to potential employers by the high-status degree, which required substantial effort to obtain [85].

Many similar selection scenarios occur in open-source development: for example, choosing which repositories to watch [121], which pull requests to accept [97], which developers to follow and receive updates from [122, 123], and which ones to recruit [110, 124]. In all these scenarios, the signals available on social coding platforms like GitHub have been shown to play a role. Our work contributes to the literature on signaling and transparency in online collaboration environments by studying another important selection scenario: *how do people use signals in transparent environments like GitHub when deciding which open-source project to contribute to.* Such signals could be found, for example, on a project's README file: READMEs already contain many highly visible cues, since GitHub renders the file by default on a project's profile page (Figure 2.2). Some of these cues could be reliable signals. For example, comparing to a short or uninformative README, a well-structured and detailed README on the usage and contributing process could show that the project owners are aware of their audience and have spent time on maintaining the project. As a result, one could expect that the owners are more willing to provide support.

2.2.3 Prior empirical evidence on how people choose projects

While prior research on this particular question is scarce, there is some empirical evidence suggesting how the different signals visible on GitHub might influence people's decision to contribute to a project. We note four studies in particular.

Dabbish *et al.* [26] reported on an interview study with 24 GitHub users of the types of inferences that people made based on the visible signals on GitHub. While the authors did not systematically pursue the question of project attractiveness to potential contributors, their findings are relevant to our research question, as some of the signals and corresponding project qualities their study uncovered could impact people's decisions to contribute to a project. Specifically, Dabbish *et al.* found that: (i) the recency of activity in a project signals project liveness and maintenance; (ii) the amount of attention a project receives, as indicated by the number of stars and watchers, signals artifact importance, project quality, and community support; (iii) a high number of open pull requests signals low conscientiousness in dealing with external contributors; and (iv) the number of forks and watchers of a project signals audience size and potential impact of contributing—this inference was the only one explicitly cited as a motivation to contribute.

More recently, and concurrently with our work, Fronchetti *et al.* [125] reported on an archival analysis of data from 450 open-source GitHub projects, studying which project characteristics are related to the growth pattern in the number of new committers per project, computed over a period of 72 weeks. The authors sampled, in decreasing order of popularity as indicated by the number of stars, 30 projects each across the 15 most popular programming languages on GitHub. Then, using a Random Forest classifier to model the growth pattern in new committers, they found that the number of stars has the highest explanatory power among all predictors considered, followed by the time to merge pull requests, project age, and the number of programming languages used in the project. On the other end of the spectrum, the presence of CONTRIBUTING, LICENSE, and CODE OF CONDUCT files, as well as the presence of issue and pull request templates, all of which are often recommended as community best practices, were among the worst ranked factors in their model. While these results offer valuable insights into which signals might be used by potential open-source contributors when choosing projects, given the choice of Random Forest classifier the directionality of the reported associations remains unknown. Moreover, it remains unknown how the results would generalize beyond the relatively small sample of most popular projects per language (the median number of stars in their dataset is 10,470); for example, the lack of explanatory power for the different community best practices such as CONTRIBUTING files or issue

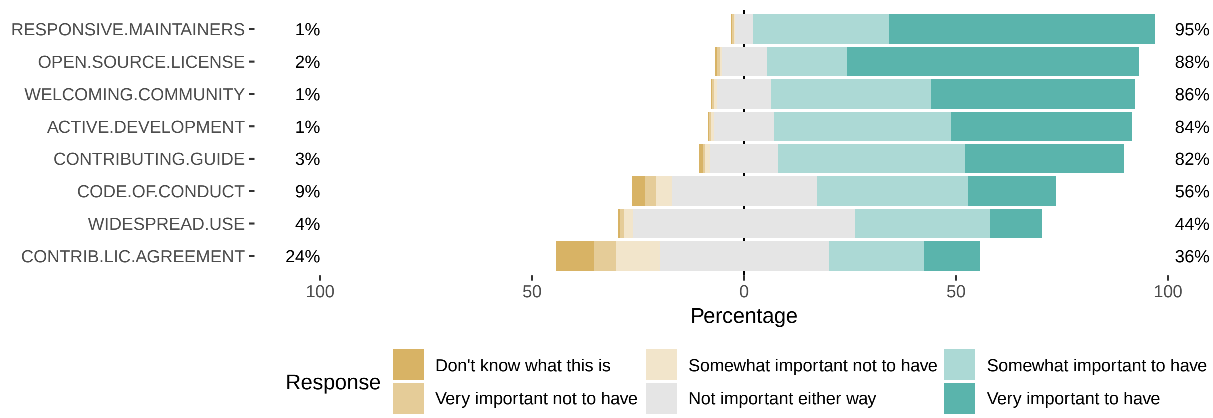


Figure 2.3: Breakdown of responses ($N = 3127$) to the question "When thinking about whether to contribute to an open source project, how important are the following things?" from GitHub's 2017 Open Source Survey [1].

and pull request templates could simply be due to the sampling strategy, as the absolute most popular projects are likely to all already implement these best practices. Finally, it is unclear how the different factors extracted from repositories have been selected. In contrast, we use a mixed-methods design to first qualitatively uncover which signals our interviewees use and how they make inferences using these signals, then quantitatively model, using multivariate regression, how the project attributes made visible by these signals associate with the likelihood of attracting new project contributors in a large sample of 9,977 projects.

We also note a study by Borges and Valente [81], who surveyed 791 developers on the meaning of GitHub stars, finding that three out of four respondents consider the number of stars before using or contributing to a GitHub project. However, in their study design the authors do not distinguish usage and contribution to GitHub repositories, so it remains unclear which signals affect which.

Finally, as part of GitHub's 2017 Open Source Survey [1], the authors asked respondents to rank several factors based on importance when thinking about whether to contribute to an open-source project: an open source license, a code of conduct, a contributing guide, a contributor's license agreement (CLA), active development, responsive maintainers, a welcoming community, and widespread use. Figure 2.3 summarizes the survey results, which are publicly available [1]: all factors are considered somewhat important or very important to have by at least 36% of respondents; maintainer responsiveness ranks as topmost important (95% of respondents).

2.2.4 Summary

In summary, potential contributors have access to a wealth of information about open-source projects on GitHub, which could act as signals for qualities that are important when deciding which project to contribute to. Some of this information is highly visible on the platform by default through built-in visible cues (*e.g.*, a project's number of stars). Project maintainers can choose to make visible other pieces of information through a project's README file (*e.g.*, a code quality badge). Finally, since for open-source projects the entire history of activity is accessible publicly (*e.g.*, all commits, issue discussions, and pull requests, together with all the actors involved), users on the platform are free to use many additional, less readily observable pieces of information when making decisions and forming impressions.

2.3 Qualitative Analysis Methods

To explore what signals people use when deciding which open-source projects to contribute to on GitHub and how the signals impacted their decisions, we first conducted semi-structured interviews with 15 GitHub users, then, based on the interview results, we mined and analyzed GitHub trace data to test the significance of each signal. Our mixed-methods strategy is *sequential exploratory* [126], as we use the quantitative results generated in a second step to assist in the interpretation of the qualitative interview findings. Here we describe the qualitative methods.

2.3.1 Interview Protocol

We developed a semi-structured interview protocol that could enable participants to evaluate a project's "attractiveness" for external contributors based on the information available on GitHub. In short, participants were asked to evaluate five given open-source projects and talk aloud about what information they were using and how that influenced their evaluations.

The main challenge in developing the interview protocol was separating the two forces that can influence the decision to contribute to an open-source project [107]: individual motivation and project attractiveness. We describe the iterative process through which we addressed this challenge.

Iterative design of the interview protocol. We started with two main design options and ran a series of pilot interviews to finalize the interview protocol: 1) asking participants about their actual *past* experience contributing to different projects, or about their intentions to contribute to new projects in the near *future*; 2) asking participants to evaluate the open-source projects for their *own* intended contribution, or for *someone else*.

In a first pilot round, we interviewed three colleagues and friends who are active on GitHub, asking participants to recollect their past experience of finding a new project to contribute to and describe their choice. The interviews confirmed the two expected shortcomings of this design: people's memory of the selection process was too vague and incomplete to be reliable; and people commonly reported choosing projects because they were using them and wanted to fix bugs or develop new features, *i.e.*, personal motivation. Since our goal was to identify a general set of advice that everyone can follow, in the next interview protocol design, we direct participants' attention to project characteristics rather than their personal interests.

To help delineate individual motivation from the effects of different GitHub signals on project attractiveness, in a second pilot round with six other friends and colleagues active on GitHub we introduced two changes. First, we employed a think-aloud technique [127], asking participants to look for a new project to contribute to while talking aloud about what signals they were considering. This allowed us to follow the participants' moment-by-moment cognitive process more precisely. Second, we changed the focus from recommendations for

Table 2.1: GitHub metrics for the five open-source projects presented to the interviewees

Project	Issues	Pull requests	Releases	Contributors	Watchers	Stars	Forks	Branches	Badges
1	2	37	216	18	18	7	3	290	7
2	334	104	46	1003	7305	124,012	59,243	29	11
3	38	0	7	6	17	214	11	2	0
4	9	0	8	1	1	1	0	2	1
5	33	4	399	7	10	8	2	9	1

oneself ("would you contribute to this project?") to recommendations for a third party ("would you recommend Jane to contribute to this project?"). In addition, each participant was given a pre-determined set of the same five JavaScript front-end projects, chosen purposefully (Section 2.3.2). Specifically, we constructed a scenario where participants were asked to make recommendations for a recent graduate with a bachelor's degree in computer science, Jane, now working for a startup as a junior front-end engineer. No information about Jane's interests, beyond JavaScript front-end, was given. Through piloting, we found that the use of the Jane persona helped alleviate the effect of participants' personal preference when choosing projects, allowing them to focus on the GitHub signals.

Final version of the interview protocol. Our final protocol maintained the semi-structured think-aloud format with the scenario of recommending projects for Jane. In addition, we also asked the participants to summarize their criteria when selecting projects and to offer suggestions for project maintainers to improve the attractiveness of their respective projects. Finally, at the end of the interview we collected basic demographics (gender, occupation, and open-source experience).

Limitations. We note that because of the scenario used in our interview protocol (making recommendations for a relatively novice developer interested in JavaScript front-end), our results may not generalize to other developers, *e.g.*, experts. We also acknowledge that (1) recommendations made for someone else can differ from choices one would make for themselves, and (2) the profile of the person onto which our interviewees made projections may itself be a source of potential bias (*e.g.*, the gendered profile of the recommendee in our protocol, Jane, may trigger biases among male interviewees). As discussed above, this study design element—recommending projects for another developer—was necessary to delineate decisions influenced by individual motivations from those influenced by project attractiveness signals. A comprehensive set of interviews, where all variables relevant to the recommendee's profile (*e.g.*, gender, level of experience, interests) are crossed, goes beyond the scope of this study, but could be a worthwhile direction for future research.

2.3.2 Project Selection

We selected five projects that collectively reflect a variety of signals possible on a GitHub page. At the time of our interviews, the values of the different project metrics were the ones shown in Table 2.1 (as of April 28, 2018). Our project selection was based on the following specific criteria:

Table 2.2: Participants' demographic information

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15
Experience	6m	12y	1m	9y	>8y	2y	4y	<2y	1y	5y	1y	1.5y	8y	3y	10y
Gender	M	F	F	M	M	M	M	F	M	M	M	F	M	F	F
Full-time dev.	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No	No

Domain. Since our persona Jane was designed as a front-end engineer, we only chose front-end-related JavaScript projects so that the participants' decisions would not be confounded by Jane's personal interest. To control for potential differences in practices and culture in different open-source ecosystems, we further required that all selected projects be part of *npm*,[1] the most popular package manager for the JavaScript programming language.

GitHub *metrics.* Activity and popularity metrics, such as the number of contributors, stars, forks, and watchers, are among the most visible cues on a GitHub repository page (high visibility signals cf. Section 2.2), since they are part of the standard UI. We chose projects to ensure high variance in these numerical metrics across our set of five: one project has a very large number of contributors (over 1,000), stars, forks, and watchers; one is a one-person project with only one watcher, one star, and no fork, and the three other projects are in between. In addition, during pilot interviews we observed that participants also paid attention to a project's pull requests, issues, and releases. In our final selection, we stratified to ensure variance along all of these as well.

Finally, we sampled such that we could include one project that had last been updated more than one month before, and thus might be considered inactive, since during pilot interviews project dormancy status seemed important. The other four projects were still active at the time.

Quality of README. During pilot interviews participants paid close attention to a project's README. To ensure variance in the README "quality" across our projects, we stratified our sample by the amount of information in (length of) the READMEs. Moreover, since prior work has shown that badges have high signaling value [27], we also sampled for variance across repository badges; our five projects range from no badge to over 10 different badges.

Limitations. Note that we tried to stratify across more dimensions than there are projects in our final sample (five total), meaning that some dimensions are confounded. This design decision was necessary to keep the interviews short.

2.3.3 Interview Participants

We sampled candidate participants from among GitHub users who had recently made pull requests to collaborative open-source JavaScript projects on GitHub, which we define as those projects involving at least three contributors, as per the public GitHub data mined from Google's BigQuery;[2] this helps exclude many "toy" projects [128] and increases the likelihood that that our interviewees are experienced open-source practitioners. Information about

[1] `https://www.npmjs.com`
[2] `https://cloud.google.com/bigquery/public-data/github`

the programming language (JavaScript) was extracted from the label that GitHub assigns automatically to each repository. As an additional data cleaning and filtering step [128], we also excluded projects we could manually label as "educational" based on keywords present in their description, *e.g.*, course number (COS496).

Then, we sent out several rounds of email invitations (123 emails total) and carried out 15 interviews via Google Hangouts or Skype, at which point we considered that we had reached theoretical saturation [129] after an informal analysis. The interviews were conducted individually and each of them took between 20 to 45 minutes. The participants were not compensated.

Among the 15 participants, the length of open-source experience ranged from one month to more than 10 years. Nine participants were full time software engineers. The occupations of the other six participants ranged from technical writer to researcher. Five were located on the US West Coast, three on the East Coast, three in Asia, one in Africa, two in Europe, and one in Oceania. Table 2.2 summarizes the participants' demographic information.

2.3.4 Data Analysis

The interviews were audio-recorded, transcribed verbatim, and coded independently by two authors. Then the coded transcripts were analyzed based on the grounded theory methodology [129]. We first identified signals mentioned by participants and how they were using these signals to make decisions. We then grouped these signals and participants' comments into categories and extracted relationships between the categories. We repeatedly discussed the categories and refined them iteratively as more interviews were conducted; this is also when we resolved a few disagreements, through discussion, between the two coders. We continued this process until new interviews did not reveal new signals that were not captured by our codes (theoretical saturation).

2.4 Interview Results - Recognizing the Signals

Our qualitative analysis identified a rich set of signals that the participants rely on when evaluating whether a GitHub project is worth contributing to by the Jane persona.

2.4.1 Website

The website link in the project description is usually the first thing the participants saw. Six participants (P1, P2, P7, P8, P10, P13) mentioned that "*the first thing I typically do is see if they have a website at all*" (P2). A website is even more important for UI libraries, to "*show a demo of what the components look like. It would be helpful to make people more interested in the project I think.*" (P10). Maintaining a good website is also recommended by many open-source practitioners.[3]

[3] https://opensource.guide/finding-users/

2.4.2 README

The README.md file is one signal that every participant commented on, *e.g.*, "*the README is a project's welcome mat*" (P14). Several aspects of the README seem important:

Structure. Prior work [130, 131] found that projects with good READMEs tend to be more sustainable and more popular. Our participants confirmed that a well structured README can give a nice first impression. P12, a technical writer, summarized that an ideal README should have a table of contents, contributing guidelines, and information on how to get in touch with the community, "*which is very very important for a newcomer*" (P12). P7 mentioned that there is an "*unofficially agreed template of a project,*" and maintainers should "*follow what everyone else is doing*" (P7).

Project description. Participants were looking for clear descriptions of the project in the README. Not being able to understand the project's goals induced negative impressions, even rejections, among some participants (P2, P7, P8, P12). For example, P7 noted that a good README *"allows [one] to understand what this project is about, how to install it, and how to use it. It also gives examples of code snippets for its API and their effects."* (P7)

Contact information. Being able to communicate with project maintainers was seen as important to contributors, especially newcomers. P2, P11, and P12 mentioned that mentioning the project's Slack channel in the README is a welcoming signal. P14 mentioned that it is nice to be able to follow the maintainer on Twitter. Having a Twitter handle is in fact suggested by some open-source practitioners. Such practices may alleviate the barrier of communication difficulties, which was identified by Steinmacher *et al.* [105], to some degree.

Code quality badges. Five participants (P3, P7, P10, P11, P14) mentioned badges but had diverging opinions about them. Some noted that the presence of badges, especially code coverage, suggests that the maintainers care about code quality (P7, P11) and that contributing to this type of project can improve one's skills (P11). In contrast, others explained that they ignore badges because "*a lot of projects have build passing badges but actually the project is broken or really out of date*" (P10).

Logo. Four participants (P5, P8, P10, P14) mentioned the Logo in the README, *e.g.*, "*They've even got a logo. That's quite promising. Because that means someone cares enough about the project.*" (P10).

2.4.3 Contributing Guidelines

Contributing guidelines, either in the README or the CONTRIBUTING.md file, were important in all participants' decision processes. Some noted that the contributing document is a decisive signal in the sense that lacking one would induce an immediate negative impression (P3, P15). In contrast, the existence of contributing files "*suggests they have some experience with handling new contributors*" (P4). Participants expect that contributing guidelines have several characteristics:

Prominent. The first thing participants mentioned about contributing guidelines is how easily they can be found (P3, P4, P5, P12, P14, P15). As per signaling theory, since potential contributors tend to prefer signals that are easier to observe and to interpret over those that are costlier to assess, it is desired to have a link to the CONTRIBUTING.md or a contributing section in the README, *e.g.*, "*the README is most important. It should describe without having to navigate away from that page the key information people need*" (P14).

Thorough. Many participants (P1, P2, P3, P10, P12, P14, P15) remarked on the contents of contributing guidelines, expecting code style guidelines and project conventions, as well as how to submit a pull request. In particular, maintainers should set the expectation by listing out things that need help and things that are allowed or disallowed. P14 also pointed out that it is nice that "*It says 'please ask first' because otherwise people might feel that the pull requests always have to be merged in*" (P14). Thorough contributing guidelines may lower the barrier of lacking knowledge about procedures and conventions, identified by Balali *et al.* [8]. Contributing guidelines should also explain the GitHub jargon, *e.g.*, "*a lot of new people who don't know GitHub don't necessarily know what the issue tracker was*" (P14). Moreover, some terms are project-specific. During the interviews, some people were confused by some terms they had not seen before, *e.g.*, "pre-commit" (P14).

However, having too detailed contributing guidelines may be perceived as too much process, especially by newcomers, who may find the instructions difficult to follow (P2, P4, P5, P10, P15). P15 summarized that "*if you are a new developer and you are just learning, you might not get this sort of hands-on response if you didn't properly submit an issue or pull request; your issue / pull request might just sit there and get closed without much explanation*" (P15). In addition, potential contributors may interpret language such as "*talk to [the maintainers] before any significant pull request*" (P2) as unwelcoming. Pull requests that do not follow project guidelines or that are considered not needed or interesting by maintainers are common barriers faced by newcomers [105].

Open to non-code contributions. Six contributors (P2, P5, P10, P11, P12, P14) stressed the importance of explicitly mentioning other acceptable types of contributions besides code, such as writing documentation. At the same time, invitations to submit issue reports without also soliciting code contributions can be seen as uninviting for someone interested in contributing more. As P12 put it: "*They only ask for filing an issue if something breaks. So I think they are more looking for people to test all these components for them, rather than asking for code contributions.*" (P12).

2.4.4 Scaffolding

Most participants commented on the guidelines for submitting issues and visited the issue trackers during the interviews. There are several signals they look for there:

Labels. Two types of labels, which we classify as technical and social, emerged as important signals. The social labels, pointing people to issues that are suitable for beginners,[4] are especially useful for newcomers. As P1 summarized, "*good open source projects would have labels like 'help wanted', 'good first issue'*" (P1). These can help contributors find their way around a new project.

In contrast, other labels can give contributors some technical information about the issue, *e.g.*, the programming language, or whether it's a bug or a feature request. Having issues clearly labeled with technical attributes can help contributors find the issues they aren't just

[4] E.g., "Good First Issue" proposed by Kent Dodds in 2015 `https://blog.kentcdodds.com/first-timers-only-78281ea47455`

able to resolve, but are also interested in working on. As one of the participants said: "*you want to work on X, and you come in and see the things that need to be done on X*" (P14), such as front-end.

Templates for issues and pull requests. Seven contributors (P1, P2, P3, P10, P12, P14, P15) noticed the templates for submitting issues or pull requests. Having a template can prevent newcomers to submit issues or pull requests that are "*stupid*" or lack information, because the "*template will take them through a bunch of different pieces of information that they need to submit*" (P14). It is a sign that shows "*there's a good structure for contributing to [this project]*" (P10).

2.4.5 Activity

Participants also look for a multitude of signals indicating the project is being actively maintained.

Number of contributors. While this was a prominent signal during our interviews, participants disagreed on what is a good team size, referring especially to newcomers. Recall that our sample comprises one large project (over 1,000 contributors), one single-person project, and the rest are small-medium sized (6, 7, and 18 contributors). A priori, we could have expected that larger projects are more likely to attract developers [132]. Indeed, among 11 participants who talked about team size, five mentioned reasons why a big project may be a better choice for newcomers. One reason is that with more contributors in the team, the project can be more sustainable. If there are only 1 or 2 people in the team, once these members leave, either the contributors' efforts are wasted or they need to take on the onerous maintenance job themselves (P6, P10, P15).

Another reason is about the mentorship opportunities one can access in big projects. Maintainers tend to be busy and they might be slow to respond to newcomers. If there is a large community, there is a higher chance that someone will be available to assist newcomers (P1, P2, P6). P2 also suggested that newcomers should avoid single-person projects because it is possible that these projects are unfriendly to external contributors (otherwise they would have more).

On the other hand, P4 and P15 listed out reasons against choosing big projects, referring mostly to the process overhead in submitting a pull request, which may intimidate newcomers. Pull request "bureaucracy" is a known barrier for newcomers [105]. However, P2 acknowledged that "*[while] the barrier to entry may be higher because the standard is higher, there are more people to help you*" (P2).

Six participants (P2, P3, P4, P5, P10, P15) suggested they prefer to start with smaller projects. One advantage of a small project is that the maintainers may be more responsive. Unlike big projects, which are "*so widely used and huge that it might take a while for maintainers to respond*" (P3), "*there's a chance that the author would be willing to reply to any pull requests you make*" (P10).

Another advantage of a small project is that contributors can get more feedback from the maintainers, which can help them improve their pull requests. Otherwise, P10 noted that "*if you have too many people, the developers don't have time to look at your individual pull* *requests. I bet that if I put a pull request, it will build fail or something and no one would care, they would just ignore it.*"

Furthermore, four participants (P2, P3, P4, P15) pointed out that smaller projects are preferable for newcomers to learn the GitHub workflow because in bigger projects "*it would be hard to figure out where to start even though things are relatively well labeled*" (P15).

Recent commits and contributors. Many participants (P1, P2, P5, P6, P7, P8, P10, P12, P13, P14, P15) suggest looking at the number of *recent* commits and contributors, rather than the total number. Otherwise, people will assume that the project is *"not under active development, because nothing has happened [for some time]"* (P14). Recency of activity signals that *"the project is not dead"* (P5).

Contributions are evenly distributed. Some participants (P2, P6, P10, P14, P15) suggest that contributors should also pay attention to whether the contributions are evenly distributed among existing team members. P6 has summarized the rationale: "*For projects of middle or small size, if contributions are evenly distributed among contributors, it is acceptable. But if only one or two people are the core contributors, then it would be dangerous; [the project may be left unmaintained]*" (P6).

This practice is also recommended by Karl Fogel. In his book *Producing Open Source Software*, he recommends to "measure commit diversity, not commit rate."[5]

Average time for responses to issues or pull requests. Another important signal is how long it takes maintainers to respond to issues or pull requests (P1, P3, P10, P11, P12, P14, P15). To make this inference, participants browsed through multiple issues or pull requests.

Numbers of open issues or unmerged pull requests and their reasons. When looking at the list of issues / pull requests, participants noted that it was important to look at the number of open issues / unmerged pull requests and why they are not resolved (P10, P11, P13, P14, P15). The reason is well summarized by P11: "*I want to know why these PRs are not merged. If I send a PR, I don't know whether or not this project is being maintained. I wouldn't want to waste the effort put in to understand their code base or write code. I don't want to write something and be treated like that*" (P11).

While the number of these unresolved issues or pull requests can be easily observed, the reasons are difficult to infer. P15 pointed out that an active project should make sure that "*either pull requests are getting merged, [or] having some kind of labeling system, so people understand why so [and it] doesn't just feel like it's lack of progress*" (P15).

Percentage of issues or pull requests by external contributors. Two participants (P10 and P14) have looked at how many issues or pull requests had been made by outsiders. Looking at only the number of open or merged pull requests can be deceiving in some cases. As P10 discovered, "*[This project has] a lot of closed PRs, which is interesting. But all are from the same person. I would say they are just using PRs as branching. They are just branches being merged.*" P14 described this type of projects as "*technically open without actually being meaningfully open*" (P14).

Responsiveness in issues and pull requests. Many participants (P1, P3, P4, P5, P10, P11, P12, P13, P14, P15) examined how fast do maintainers respond to issues and pull

[5] https://producingoss.com/en/evaluating-oss-projects.html

requests. Their expectations are summarized by P14: "*[An] active project [should have] some conversation happening, and generally it has been positive and ideally with reasonably quick responses. It doesn't have to be lightning quick. But more than three days between responses is not a great place to start*" (P14).

Another signal that active discussions give is the mentorship and learning opportunity offered by code review. As one participant puts it, code review is "*pretty good because you will need to follow their appropriate code style. That's an important code style. Being able to integrate [code] into their own system is a useful skill to have*" (P10).

2.4.6 Code quality

Eight participants (P4, P7, P9, P10, P11, P12, P13, P14) examined the code quality during their evaluation. One signal they look for is the presence of tests. As P7 put it, "*I wouldn't use component libraries without unit tests*" (P7). Another signal they paid attention to is the use of continuous integration (CI), especially in big projects. As P14 noted, "*If the developers can't reply immediately, it's helpful to have a CI that tells you if your code works, and if the code style is ok or not*" (P14). Two participants (P10, P13) also looked at the structure of the code itself, commenting on the importance of modularity, which makes it easier for people to understand. P9 mentioned the size of the code, which may affect whether people would use the library.

2.4.7 Popularity

The number of stars and the number of downloads of a project reflect the project's popularity. Although nine participants (P1, P3, P4, P5, P7, P8, P10, P11, P13) commented on the number of stars, only three (P1, P5, P10) mentioned that the popularity may influence their decisions. Both P1 and P10 mentioned the potential impact of contributing as an important motivation, *e.g.*,: "*Everyone uses [project X]. If you contribute to it your change is gonna have a huge impact.*" (P1) Moreover, P5 mentioned that "*if this [project] has tons and tons of stars, and there weren't that many contributors, I would think they weren't super friendly to new people*". However, P7 acknowledged that the number of stars can be faked, therefore it is not an entirely reliable signal. P3 also explained that she would not worry about popularity, because a less popular project "*gives you more self-efficacy that forces you really to look at things, google things, try everything out, and then ask for help*" (P3).

2.4.8 Community Openness

Five participants (P1, P2, P3, P5, P15) remarked on the openness of the community, as it transpires through the language used, *e.g.*, in the project documentation and issue discussions.

Language in contributing docs. Three participants noted the gender exclusiveness of the language in documentation, referring to one project which talks about "*nice guys*" that will review and merge pull requests when describing how to contribute. Two participants voiced concerns about the gender inclusiveness of this phrase. As one of the participants suggested, projects should "*avoid language that uses 'guys' or assumes that people are [all] one gender or one demographic*" (P15).

Participants also mentioned the language exclusiveness towards newcomers. Although no one identified any instance of aggressive expressions towards newcomers, some did mention that they would "*look at the language throughout to feel whether it's inclusive or it feels maybe a bit of a boy's club or sort of aggressive, or intimidating for beginners; these would make me stay away*" (P15).

Two participants also noted that "don't" may sound intimidating. Phrasings like "*'please do this', 'you are welcome to do that', by turning the language around*" are recommended instead (P15).

Conversations in issues or pull requests. The openness of the community can also be inferred from these conversations. According to P3, a good conversation should be "*commenting back and forth, [...] pretty thorough. I think it's helpful. No one is mean necessarily*" (P3). Sometimes, not following the process can "*get people mad at you*" (P5).

Code of conduct. The presence of a code of conduct signals a welcoming community. One participant told us that "*This project has a code of conduct, and they've adopted the standard contributor covenant.*[6] *So my belief is that this would be a welcoming community because people are conscious of having a code of conduct*" (P2). Being kind to contributors has been encouraged by many people and organizations. For example, Scott Henselman posted a blog in 2015 that pledged people to treat newcomers nicely, including writing a contributing guideline, tagging issues that are good for newcomers, and having a code of conduct.[7] Prior research by Tourani *et al.* [133] has also discussed the importance of having a code of conduct; however, only relatively few projects have them, though they are becoming increasingly common [133].

Gender representation. Two female participants pointed out that the gender balance among the existing contributors, as inferred from their GitHub profile information, might be a potential barrier to female newcomers. More specifically, they both pointed out that a medium size group (in our case, the project has 5 contributors) of male contributors may form a clique that a female contributor could have difficultly breaking into. However, if the project's only contributor is a man, then it is "*not as difficult a community to break into as a group of men.*" (P14). In addition, for large projects with hundreds of contributors, "*because there are so many people contributing, it doesn't matter so much whether it's all male*" (P14). As the other participant summarized: "*If I saw a project where it seems like a mix of genders, I would definitely feel more excited about the project*" (P15).

2.5 Quantitative Analysis Methods

To triangulate our interview findings, we set out to quantitatively test the overall hypothesis that the signals we identified from the interviews are indeed associated with attracting more new contributors. We collected a large dataset of open-source GitHub projects, operationalized the signals uncovered during our interviews, and used multiple regression analysis to model the association between the different signals and the likelihood of attracting new project contributors (binomial logistic regression), as a way to validate the perceived importance of each signal.

[6] https://www.contributor-covenant.org/

[7] "Bring kindness back to open source" https://www.hanselman.com/blog/BringKindnessBackToOpenSource.aspx

The multivariate regression analysis seeks to uncover whether any (and which) project characteristics and signals, observed over a fixed period of time (details below) help explain the average differences between projects in likelihood of attracting new contributors, as observed over a subsequent fixed period of time. The multivariate nature of the regression modeling enables us to quantify the strength of the association between each explanatory variable and the binomial outcome while *adjusting for other covariates*, *i.e.*, removing confounding effects.

Specific hypotheses. Based on the interview results, we hypothesize that other variables held fixed, open-source projects are more likely to attract new contributors when: they list a project website (H_1); are more popular (H_2); are active (H_3); have a comprehensive README (H_4); list the owners' contact information or support channels, *e.g.*, Twitter, Slack (H_5); include badges reflecting code quality (H_6); include CONTRIBUTING instructions (H_7); label their issues to help steer contributors (H_8); provide issue or pull request templates (H_9); have fast response times to pull requests (H_{10}); and are welcoming towards newcomers (H_{11}).

Data. We collected a sample of 9,977 open-source JavaScript libraries published on the npm package registry[9] and available publicly on GitHub as follows. We started from a pre-existing list of the 50,000 npm packages with the most GitHub stars (min 6, median 69, max 70,266) and further randomly sampled another 2,000 npm packages with at most 6 stars as of June 1st 2018 (when the other data ended), to better stratify the data. Next, we used GHTorrent [84] to identify which of these projects: (1) were not forks of another repository; (2) had at least one commit between January 1st 2018 and June 1st 2018, to filter out completely inactive projects; (3) had non-empty README files; and (4) had at least one issue / pull request on GitHub, with at least one comment, to ensure that our measures of maintainer responsiveness and politeness (see discussion in Sections 2.4.5 and 2.4.8, respectively) are not undefined.

Measures. For each project, we used the GitHub API and GHTorrent to measure the set of variables in Table 2.3 (summary statistics in Table 2.5). The response variable in the regression models is a boolean flag *has new contributors*; see table for definition. The table also describes the main explanatory variables used, corresponding to the specific hypotheses above. In addition, we tested the presence of three interaction effects between project size / level of activity and having contributing guidelines, badges, and a link to a project website, respectively; see table for rationale.

Modeling considerations. We built two multivariate binomial logistic regression models corresponding to the two versions of our binary response variable *has new contributors*: one for any new pull request submitters and one for new pull request submitters that are also new to GitHub, not just the given project.

In each case, we log-transformed variables, as needed, to reduce heteroscedasticity [135] (Table 2.4 lists which variables were log-transformed). We also tested for multicollinearity using the variance inflation factor (VIF), comparing to the recommended maximum of 5 [136] (Table 2.6); no variable exceeded the threshold. We assess the goodness of fit of the regression models using McFadden's pseudo R^2 measure [137] (Table 2.4). Finally, we report the regression coefficients together with their p-values and estimates of their effect sizes (units of variance explained) from ANOVA analyses (Table 2.4); odds ratios for the different factors can be obtained by taking the exponential of the regression coefficients.

[8] The first page of closed issues on a project's GitHub profile shows 30 entries.

[9] https://www.npmjs.com

Table 2.3: Overview of the different variables we computed and modeled.

Variable	Signal	Definition / Rationale
		RESPONSE VARIABLE
Has new contributors	§2.4.5	Boolean flag measuring presence of new pull request submitters between June 1st 2018 and September 1st 2018. To test the sensitivity of our analysis to this operationalization, we distinguish between new contributors *with* (model "Any new contributors" and hypotheses $H_{1\ldots11}$) and *without* (model "GH first-timers only" and hypotheses $H'_{1\ldots11}$) GitHub experience in other projects prior to the current one.
		CONTROL VARIABLES
Has external committers	§2.4.5	Boolean flag indicating if there were commits made by non-core contributors; core is defined as people each authoring at least 5% of the commits from January 1st 2018 to June 1st 2018. Controls for general openness of the project to newcomers.
Project age		The age of the project on June 1st 2018, in days. Controls for software evolution: a project in a developing stage may have more issues for new contributors to work on than a mature one.
Num issues	§2.4.5	Total number of issues (not including pull requests) on June 1st 2018. This number is a highly visible signal at the top of a GitHub project's main page. Projects with more issues are likely to have more work available for contributors, as well as larger potential contributor pools.
		MAIN EXPLANATORY VARIABLES
Has website (H_1, H'_1)	§2.4.1	Boolean flag indicating if the project contains a homepage URL.
Num stars (H_2, H'_2)	§2.4.7	The number of stars on June 1st 2018 as per GHTorrent, as a proxy. for project popularity.
Num recent commits (H_3, H'_3)	§2.4.5	Total number of commits from January 1st 2018 to June 1st 2018, as a proxy for project activeness.
Num headers (H_4, H'_4)	§2.4.2	The number of markdown headers (H1–H3) in the README, as a proxy for comprehensiveness.
Has contact info (H_5, H'_5)	§2.4.2	Boolean flag indicating if the README contained references to a Twitter handle or Slack channel.
Has badges (H_6, H'_6)	§2.4.6	Boolean flag indicating if the README contained code coverage or continuous integration badges.
Has contrib (H_7, H'_7)	§2.4.3	Boolean flag indicating if the repository contained a CONTRIBUTING.md file or if the README contained a section on how to contribute.
Has labels (H_8, H'_8)	§2.4.4	Boolean flag indicating if the project has labels applied on issues or pull requests.
Has template (H_9, H'_9)	§2.4.4	Boolean flag indicating if templates were used for submitting issues or pull requests.
Is fast (H_{10}, H'_{10})	§2.4.5	Boolean flag indicating if the median response time to the the 30[8] most recently opened issues which were closed as of June 1st 2018 is below the first quartile of projects. Responses count if a non-obviously-bot user nor the issue author comments or performs an action on the issue.
Is impolite (H_{11}, H'_{11})	§2.4.8	Boolean flag indicating if the project's median impoliteness score ranks in the top quartile across our sample. We collected impoliteness scores for the comments in the first page of closed issues as seen on June 1st 2018 using the Stanford Politeness API [134], after removing markdown formatting and replacing each code block with the token "`CODE.`".
		INTERACTIONS
Has contrib × Num recent commits (H_7, H'_7)		Contributing guidelines may impact larger, more active projects differently, as there could be more need for help navigating project norms and processes.
Has badges × Num recent commits (H_6, H'_6)		Badges displaying negative project qualities, *e.g.*, broken build, may create more negative impressions the less active the project is, making it appear abandoned.
Has website × Num recent commits (H_1, H'_1)		A potentially broken link, more likely to occur in a less actively maintained project, may increase the appearance of abandonment.

Table 2.4: Summary of logistic regression results showing which signals associate with new contributors.

	Any new contributors Response: *has new contributors* Pseudo $R^2 = 20\%$		**GitHub first-timers only** Response: *has new contributors* Pseudo $R^2 = 21\%$	
	Coeffs (Err.)	Deviance	Coeffs (Err.)	Deviance
(Intercept)	$0.79\ (0.47)$		$-1.93\ (0.75)^{**}$	
has external committers	$0.60\ (0.06)^{***}$	88.54^{***}	$0.36\ (0.10)^{***}$	11.95^{***}
project age (log)	$-0.60\ (0.07)^{***}$	80.25^{***}	$-0.50\ (0.11)^{***}$	22.18^{***}
num issues (log)	$0.43\ (0.03)^{***}$	236.81^{***}	$0.56\ (0.05)^{***}$	140.38^{***}
has website	$-0.43\ (0.10)^{***}$	19.80^{***}	$-0.17\ (0.17)$	0.92
num headers (log)	$0.10\ (0.03)^{**}$	9.59^{**}	$0.08\ (0.05)$	2.06
has contact info	$-0.12\ (0.07)$	2.86	$-0.03\ (0.10)$	0.10
has contrib	$-0.31\ (0.11)^{**}$	0.76	$-0.46\ (0.20)^{*}$	10.14^{**}
has badges	$0.14\ (0.09)$	1.51	$-0.49\ (0.16)^{**}$	6.79^{**}
has labels	$-0.13\ (0.05)^{*}$	6.19^{*}	$-0.08\ (0.09)$	0.84
has template	$0.48\ (0.16)^{**}$	9.11^{**}	$0.25\ (0.16)$	2.52
num recent commits (log)	$0.12\ (0.03)^{***}$	62.53^{***}	$0.07\ (0.05)$	38.66^{***}
is fast	$-0.04\ (0.06)$	0.52	$-0.10\ (0.09)$	1.04
num stars (log)	$0.21\ (0.02)^{***}$	97.53^{***}	$0.14\ (0.03)^{***}$	17.02^{***}
is impolite	$-0.32\ (0.07)^{***}$	20.99^{***}	$-0.08\ (0.12)$	0.43
has contrib : num recent commits (log)	$0.11\ (0.04)^{**}$	7.18^{**}	$0.05\ (0.05)$	0.87
has badges : num recent commits (log)	$-0.04\ (0.04)$	1.11	$0.10\ (0.05)^{*}$	4.05^{*}
has website : num recent commits (log)	$0.09\ (0.04)^{*}$	6.24^{*}	$0.09\ (0.05)$	3.01
AIC	10442.37		4694.43	
Num. obs.	9977		9977	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

2.5.1 Replication Package

Our data collection and data analysis scripts, and the input data for the regression models in Table 2.4, are part of a replication package available online.[10]

2.6 Regression Modeling Results - Triangulating the Signals

In this section we discuss the quantitative analysis results for our main model ("Any new contributors" in Table 2.4). We further test the robustness of our results to the operationalization of *new contributors* by modeling "GitHub first-timers only" as the dependent variable (Table 2.4). Both models have acceptable goodness of fit (20%–21%). We will contrast the qualitative and quantitative results and discuss implications of our results later, in Section 2.7.

[10] https://doi.org/10.5281/zenodo.3371186

2.6.1 Attracting any new contributors

From Table 2.4 (model "Any new contributors"), we first observe that the control variables expectedly account for around 60% of the variance explained by the model (sum of the cell values corresponding to the control variables in the Deviance column in the table, divided by the total amount of Deviance explained by the model, *i.e.*, sum over all rows), with predictable effects: projects with more open issues (signaling contribution opportunities [26]) or that are younger or historically more open to newcomers are more likely to attract additional new contributors, on average.

Moving on to the main explanatory variables, we observe that projects with more GitHub **stars** (supporting H_2 ✓), more **recent commits** (signaling the project's activity level [26]; H_3 ✓), more **comprehensive README files** (more headers; H_4 ✓), and having **issue or pull request templates** (H_9 ✓) are statistically significantly more likely to attract new contributors, supporting our hypotheses and the qualitative data collected during the interviews. Taken together, the four variables account for approximately 27% of the total variance explained by the model.

Among these variables, the number of GitHub stars, a signal of project popularity, explains the largest amount ($\simeq$ 15%) of the total variance explained by the model. We illustrate the interpretation of the regression coefficient: for every factor e increase in the number of stars (note the log-transform), and after controling for the amount of project activity and other covariates, the odds of attracting new contributors for the average project in our sample increase $\exp(0.21) \simeq 1.23$ times. Fronchetti *et al.* [125] found, similarly, that project popularity is the most important factor that explains newcomers' growth pattern.

The first model also shows that the number of recent commits explained a large amount ($\simeq$ 10%) of total variance explained by the model. As some of the participants pointed out and also discussed by Dabbish *et al.* in [26], the number of recent commits signals the projects' activity level and contributors' commitment to a project. More recent commits in a project signals that there are active contributors who could provide help or feedback if needed. Therefore, programmers may be more willing to join the project.

Arguably, all four of these signals (stars, recent commits, comprehensive READMEs, and templates) have relatively high production costs, as they require deliberate and in some cases sustained efforts (*e.g.*, sustained commit activity over time) from project core developers to maintain. Given this production cost, signaling theory predicts that the signals are reliable. Our quantitative results are consistent with this prediction.

Table 2.4 also shows that posting a **website URL** (H_1 ✗), having **contributing guidelines** (H_7 ✗), using **issue labels** (H_8 ✗), and being **impolite** (H_{11} ✓) have, on average, statistically significant negative effects on attracting new contributors. The effect sizes are, however, relatively small: taken together, the four variables explain $\simeq$ 9% of the total variance explained by the model.

It is not surprising that being impolite correlates with lower likelihood of attracting new contributors: Balali *et al.* [8] found that a "harsh project atmosphere" is one of the main barriers that a newcomer faces. However, it is surprising that having a website URL, contributing guidelines, and issue labels correlates with lower likelihood of attracting new contributors.

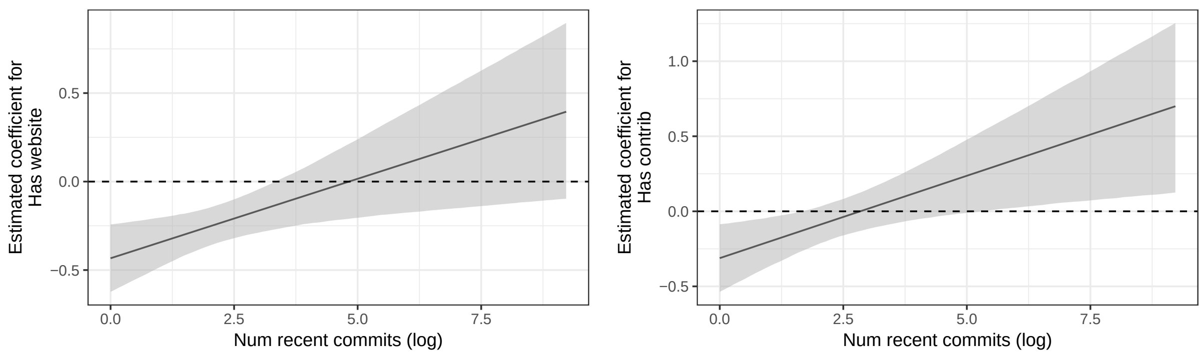


Figure 2.4: Visualization of the interaction effects Has website (left) / Has contrib (right) × Num recent commits.

The interaction effects (Figure 2.4) with the number of recent commits for two of the variables, *has website* and *has contrib*uting guidelines, suggest a more nuanced interpretation. For the *has contrib*uting guidelines dummy (Figure 2.4 right), the estimated coefficient is negative for low values of *num recent commits* but positive for high values. That is, for the less active projects, having contributing guidelines correlates with lower likelihood of attracting new contributors, holding the other variables fixed; but for the more active projects the relationship flips, and having contributing guidelines correlates with higher likelihood of attracting new contributors, as hypothesized.

For the *has website* dummy (Figure 2.4 left), the estimated coefficient is only negative for low values of project activity (*num recent commits*), and is otherwise indistinguishable from zero. That is, only for the less active projects having a website URL correlates with lower likelihood of attracting new contributors, holding the other variables fixed, whereas for more active projects having a website URL has no effect. One explanation could be that the websites of smaller, less active projects may be more often out of date or unmaintained, accentuating potential negative first impressions. Another explanation could be that unobserved third variables are confounding the association. More research is needed to better understand this relationship.

For the *has labels* dummy, we did not theoretically expect an interaction effect, therefore we did not test for one. Still, the negative effect of having labels might be explained by a limitation of our operationalization: due to lack of uniformity in how "good first issue" labels are named across projects, we only recorded a binary flag of whether a project has any labels at all, as a proxy, while it could be that only labels similar to "good first issue" have the hypothesized positive effect on attracting new contributors. Future work could refine our operationalization.

Finally, we note from Table 2.4 that having **contact information** (H_5 ✗), **code quality badges** (H_6 ✗), and **fast reponses** (H_{10} ✗) to issues or pull requests do not have statistically significant effects, contrary to our hypotheses.

2.6.2 Attracting first-time GitHub contributors

The "GitHub first-timers only" model in Table 2.4 uses as dependent variable the presence of first-time contributors, who have never made any GitHub contribution before. This alternative operationalization enables us to assess the robustness of our results and study whether contributors without any public traces of open-source GitHub experience might look for different signals when evaluating projects. Such differences could be the signals that are more reflective but unknown to first-time contributors either due to the contributors' own lack of experience or the signals' low visibility. They could also be signals that are only relevant or important to first-time contributors. Since the Jane persona we provided to participants was designed to be a first-time contributor and participants were projecting their own experience onto her, comparisons between the two models can also help to differentiate participants' projection and first-time contributors' own decision.

A comparison between the two models shows that the **number of stars** remains a strong positive predictor of attracting newcomers (H_2 ✓): the more popular a project, the more likely it is on average to attract newcomers. In addition, having **contributing guidelines** has significantly negative effect when attracting first-time GitHub contributors (H_7 ✗). However, most of the effects of the main explanatory variables have changed. Having **badges** has a statistically significant but negative effect (H_6 ✗). The interaction effect with recent project activity is also statistically significant and behaves similarly to the *has website* (left) interaction in Figure 2.4: the negative correlation between having code quality badges and likelihood of attracting new contributors is only visible in less active projects. We speculate that using CI and showing code quality badges may increase the process overhead and barrier to entry, and could be discouraging to first-time contributors, who may not have sufficient CI experience.

Other signals have statistically insignificant effects in the second model: the number of **recent commits** (H_3 ✗), having a **website URL** (H_1 ✗), **contact information** (H_5 ✗), the **number of headers in the README** (H_4 ✗), **labels** (H_8 ✗), **templates** (H_9 ✗), **fast responses** (H_{10} ✗), and **politeness** (H_{11} ✗). Signaling theory offers one possible explanation: these signals are not visible enough, therefore receivers, in this case, first-time GitHub contributors, might prefer signals that are easier to observe and to interpret. The number of recent commits is not a directly visible signal, rather it requires combining the number of commits and the last commit date. Similarly, labels and templates do not typically appear on the main page. For example, templates usually show up only when users begin to compose an issue or a pull request. Finally, evaluating the politeness and responsiveness of a project also requires contributors to look into documentation and conversations. It is also possible that new contributors lack a benchmark of politeness as a reference and may consider potentially impolite interactions as the norm; however, as they meet more people, they gradually become aware of the culture of a project and try to avoid impolite teams.

2.6.3 Commonalities and discrepancies between interviews and models

The project's popularity, signaled by the number of GitHub **stars**, and having a **contributing guideline** are the only explanatory variables that had consistent effects between our two models, which aligned with the interview results.

In the other cases, we found interesting discrepancies between the interviews and regressions. Particularly notable is the **responsiveness** which was expected to be important signal both according to interview participants as well as GitHub's 2017 Open Source Survey [1] results (Figure 2.3), but shows no results in the regression.

The negative correlation between having contributing guidelines and likelihood to attract new contributors in less active projects (recall the interaction effect above) warrants further investigation. One possible explanation is a limitation of our experimental design: contributing guidelines may have had stronger, positive effects closer in time to when they were introduced in each project, but our fixed window of observation (June 1st to September 1st 2018) hides this. Further investigations go beyond the scope of this paper, but could be a worthwhile direction for future research.

Beyond threats to construct validity (our operationalization of responsiveness of the core team could be imperfect), signaling theory offers one possible explanation for the lack of noticeable effect for the responsiveness variable. Even if potentially reliable and hard to fake (*i.e.*, an assessment signal), the signal is not plainly visible on a project's main page. While in our interviews some participants did click through individual issues or pull requests pages to estimate the response time, in a less artificial setting people may not spend as much time on evaluating projects and may rely on more visible signals instead. More research is needed to understand whether the lack of hypothesized effects is due to limitations in our operationalizations or other causes.

2.6.4 Limitations

We now note some important limitations of our quantitative study. We discussed limitations of our qualitative analysis previously, in Section 2.3.

First, we computed a set of proxies (Table 2.3) to operationalize the different theoretical constructs emerging from the qualitative analysis. While our variables are arguably reasonable measures for the theoretical constructs they are meant to capture, and even though we manually inspected and iteratively corrected data collection errors, as needed, until we were confident that our data is correct, it is important to note that other operationalizations for the same concepts are possible. For example, for the response variable one could also consider other contributions besides pull requests. Different operationalizations may lead to different statistical modeling results and therefore different conclusions. We described clearly our assumptions and operationalizations and we provide a replication package[10] to facilitate future extensions to our work. Exhaustively computing and testing multiple operationalizations for each construct goes beyond the scope of this paper.

Second, the GitHub data we mined and analyzed are observational in nature, hence the different signals we considered are not true experimental treatments. This could create endogeneity problems [138, 139], which could lead to biased estimates of the treatment effects in our regressions.[11] Endogeneity could manifest in several ways. For example, even though prior work and our qualitative analysis both suggest that higher number of stars may drive higher numbers of contributors to a project, it is also possible that an unobserved variable may jointly determine both high number of stars and high number of contributors, or that both might be true. The association between the number of stars and the likelihood of attracting new contributors, surfaced by our models, may not allow readers to conclude this correlation is causal, because observational data is not randomly assigned. Moreover, endogeneity can be caused not only by omitted variables, but also by some of the regression variables used. In our study, the number of stars a project has is endogenous when examining the quality of projects or the intent to contribute to it. When a project has a higher number of stars it may attract more contributors, but it is also likely that a project which has a high number of contributors, may attract more stars.

Endogeneity has received much attention in the econometrics literature and many statistical approaches have been proposed to assess or control its impact. Perhaps the most popular approach we considered is to instrument for the possibly endogenous predictor variable [140], in our case *number of stars*. Given such instrumental variables, one then typically pursues an estimation method such as two-stage least squares (2SLS) [141]. The basic idea is to extract variation in the possibly endogenous predictor that is independent of the unmeasured confounders and use this variation to estimate the treatment effect and "control" for the unmeasured confounders. Many extensions to non-linear models such as logistic regression, which we use in our study, have been proposed [142, 143, 144, 145, 146]. However, we decided against two-stage methods for several reasons: i) these methods are only as good as the exogenous instrumental variables selected [147, 148, 149] and we could not identify appropriate, theoretically motivated instruments for number of stars; and ii) with large sample sizes, as in our case, the estimated coefficient for the residuals is more likely to reach statistical significance, *i.e.*, it becomes more likely to falsely detect endogeneity [150, 151].

Instead, we limit ourselves to checking for correlation between the possibly endogenous number of stars variable and the logistic regression residuals. Neither model had statistically significant Pearson's product-moment correlation: $p = 0.86$ for GitHub first-timers only and $p = 0.94$ for any new contributors. Although our models explain only around 20% of the variance in the data, suggesting there may be omitted variables, we did include in the regressions variables corresponding to *all* of the theoretical constructs emerging from the interviews, in addition to controls for the obvious covariates. Therefore, based on the lack of correlation between the possibly endogenous number of stars variable and the logistic regression residuals we believe that the relatively low explanatory power of our models is more likely due to natural noise in the data, common at this scale and in this domain [128], rather than omitted important variables that could cause endogeneity.

Alternative analysis techniques such as propensity score matching, which can help reduce the risk of endogeneity [152], or recent heuristics [153] for evaluating the robustness of results to omitted variable bias, based on coefficient movements after inclusion of controls and movements in R-squared values, go beyond the scope of this paper but could be worthwhile future directions.

[11]We kindly thank one of the reviewers for pointing this out and suggesting mitigation strategies. This paragraph incorporates the reviewer's comment almost verbatim.

2.7 Implications

Our study has implications for open-source maintainers, platform designers, and researchers.

2.7.1 New Signals

Among the information our participants needed to inform their evaluation of contribution worthiness for each open-source project in our sample, only some is readily observable from prominent signals displayed on a project's landing page or README file on GitHub. For example, the *number of stars*, a proxy for project popularity, and the *number of contributors*, measuring team size, are already part of the GitHub UI. However, other pieces of needed information can be much less salient. Some, like the *number of downloads*, which indicates not only popularity but also the size of the user base, have direct signals, but these are not typically visible on GitHub directly. For example, in the case of projects with releases published on npm, the number of downloads is displayed on a package's npm page, but not on its GitHub repository page by default. We learned from the interviews and our models that popular projects tend to attract more new contributors. Badges such as downloads 654/month could be used to augment a project's existing GitHub popularity signals (the number of stars), making project popularity information more salient.[12] Trockman *et al.* [27] found that badges can impact perceptions of open-source projects.

Some other pieces of information used by our interview participants and having statistically significant effects in our models currently have no direct signals at all and, instead, need to be inferred from indirect cues. The *tone of the community*, for example, is an important factor in our interviews: "*it's most important that the people seem nice*" (P5). From the first regression model, we can see that (im)politeness also has a statistically significant effect. In our interviews some participants had to browse through multiple issues and pull requests, reading the discussions therein. If these conversations were positive (P14) and people were not mean (P3), participants concluded that the community is probably friendly and welcoming. As discussed in Section 2.2.2, signaling theory explains that assessment signals, which are costly to produce / fake, tend to be reliable. A signal of the tone of a community would arguably be an assessment signal and therefore be reliable, as maintaining a welcoming tone would require sustained effort from project maintainers over time. However, signaling theory also explains that receivers (the potential contributors evaluating projects) tend to prefer signals that are easy to observe and to interpret over those that are costlier to assess [118]. This suggests that automated techniques could be used to develop new signals of the tone of a community, *e.g.*, in the form of badges, to further increase transparency and make these important underlying qualities salient. Recent advances in detection of emotions [154], politeness [155], and sentiment [156, 157, 158] suggest that this approach is feasible.

Similarly, we envision assessment signals of the responsiveness of the project maintainers, *e.g.*, displaying the average response times to issues and pull requests submitted by external contributors. Even though our models did not validate the importance of this signal, maintainer responsiveness showed up prominently in our interviews and is also well-supported as a desirable project quality by prior work (see Section 2.2.3).

[12] GitHub's recent "Used by" button `https://twitter.com/github/status/1131468413983961088` is similar.

We also uncovered a range of best practices and associated signals that our interview participants noted help create good first impressions when evaluating a project for potential contribution: listing an external project website, having a detailed README file, including information on how to contribute, listing contact information for the maintainers, and using labels and issue / pull request templates to help newcomers learn the project processes and norms. Two of these signals, denoting the comprehensiveness of the README file and the presence of templates, we were also able to validate quantitatively. In terms of production cost, a well thought-out README file is arguably the most expensive, as it requires a high initial investment to develop and subsequent sustained maintenance to keep it up-to-date. Signaling theory predicts that this investment is worthwhile though: our study finds using mixed methods that projects with more detailed READMEs are more likely to attract new contributors.

Finally, we identified some conventional signals that project owners could consider adopting, as they are perceived to attract new contributors. Our interviews suggest that potential contributors are receptive to explicit requests for help, yet typically there is no associated highly visible signal at the project level. One of the recommendations for maintainers that our participants repeatedly mentioned is explicitly expressing that they want help and welcome contributions. There are multiple ways in which this intent can be expressed more visibly, including explicit language in the README such as "Accepting PRs" or the equivalent badges PRs welcome and help wanted. While such conventional signals are expectedly less reliable as per signaling theory since they are less costly to fake, they are still cheap to produce and may contribute to creating the impression of a welcoming community.

However, it is also possible for there to be too many signals on a GitHub project's page. Prior work by Trockman *et al.* [27] found a non-linear association between the number of repository badges displayed and the number of downloads, after controling for covariates, *i.e.*, projects with "too many" badges tend to be less popular. More research is needed to understand the situations with too many signals beyond badges, and whether some existing signals could be removed.

2.7.2 Personalized Design

During our interviews, we anecdotally observed that different contributors may interpret the same signals differently. For example, P15 explained: "*a lot of [project selections] depend on your confidence. So when it's a bigger project, are you are someone that feels comfortable jumping into the middle of things or you need a little bit more hand-holding or welcoming into the project, then it feels like this is probably the one that is easy to wander around but doesn't have the capacity to personally welcome you and help you figure out where to start*" (P15). In contrast, P3 noted that "*I don't worry about the popularity of the project because I feel like if you find things less saturated, you actually benefit more from it. There's less hand holding and you get to really dive in; it gives you more self-efficacy that forces you really to look at things, google things, try everything out, and then ask for help*" (P3).

The GenderMag literature [29] shows that groups of people that tend to differ along four problem-solving facets also tend to experience different barriers to technology and tend to use software differently [159, 8]. The facets are motivation (intrinsic vs extrinsic), computer self-efficacy (high vs low), information processing style & tinkering (reading documentation upfront vs tinkering), and attitude towards risk (high vs low risk aversion). It is possible that GitHub contributors who tend to differ along the four problem-solving facets (often gender is an attribute that people who differ along these dimensions cluster on) would also interpret the different signals differently. For example, the two quotes above suggest potential differences in interpretation of signals depending on one's self-efficacy level. This suggests that future work could take individual differences in problem-solving style into account when developing new signals, to better account for how contributors might interpret the same signals differently, *e.g.*, using the GenderMag [29] process.

2.8 Conclusions

In this chapter we used mixed methods to explore how open-source contributors decide whether or not to recommend submitting pull requests to different open-source projects based on the signals available on the project's GitHub webpage. Qualitatively, we interviewed 15 GitHub contributors about their project selection process and the signals used to inform this decision. Quantitatively, we estimated two logistic regression models using trace data from 9,977 GitHub projects, to validate each identified signal from the interviews.

Among our main findings, we highlight that contributors make inferences based on a multitude of signals, including how actively maintained and popular the project currently is, the friendliness and responsiveness of the maintainers in issue and pull request discussions, the availability of issue and pull request templates and issue labels, and a well-structured and thorough README which includes contributing guidelines. However, not all these signals are currently easily observable, *e.g.*, inferring the welcomeness and responsiveness of project maintainers involves multiple steps.

This work has direct implications for open-source maintainers and the design of social coding environments: both sets of stakeholders could focus on developing reliable new signals for the less readily observable project qualities we identified as important. Ultimately, these signals could help direct contributor effort to open-source projects where this effort is most needed, contributing to the sustainability of open-source ecosystems as a whole.

A notable limitation of our study as a whole is that controlling for topic (all projects used in the interviews are front-end-related JavaScript projects) makes it impossible to determine how important topic was compared to the identified signals. Future work should explore alternative research designs. Future work should also consider refining our operationalizations and replicating these findings on other projects that are not part of npm.

Appendix

Table 2.5: Summary statistics for the variables in Table 2.3.

Statistic	Mean	St. Dev.	Min	Median	Max
Has any new contributors	0.36	0.48	0	0	1
Has first-time-GH contributors	0.09	0.28	0	0	1
Has external committers	0.28	0.45	0	0	1
Project age	1,334.66	538.95	571	1,214	3,830
Num issues	105.45	404.52	0	22	13,198
Has website	0.35	0.48	0	0	1
Num headers	11.09	10.78	1	8	262
Has contact info	0.14	0.35	0	0	1
Has contrib	0.22	0.41	0	0	1
Has badges	0.57	0.50	0	1	1
Has labels	0.53	0.50	0	1	1
Has template	0.03	0.17	0	0	1
Num recent commits	32.86	173.44	1	6	10,087
Is fast	0.25	0.43	0	0	1
Num stars	593.95	2,464.59	0	72	70,266
Is impolite	0.16	0.37	0	0	1

Table 2.6: VIF multicollinearity test values for the variables in Table 2.3.

	Any new contributors	GH first-timers only
Has external committers	1.48	1.67
Project age (log)	1.22	1.28
Num issues (log)	2.50	3.33
Has website	1.14	1.18
Num headers (log)	1.06	1.06
Has contact info	1.06	1.09
Has contrib	1.13	1.22
Has badges	1.05	1.07
Has labels	1.13	1.25
Has template	1.04	1.09
Num recent commits (log)	1.48	1.77
Is fast	1.01	1.01
Num stars (log)	2.08	2.45
Is impolite	1.03	1.03

Chapter 3

Sustained Participation

*Sustained participation by contributors in open-source software is critical to the survival of open-source projects and can provide career advancement benefits to individual contributors. However, not all contributors reap the benefits of open-source participation fully, with prior work showing that women are particularly underrepresented and at higher risk of disengagement. While many barriers to participation in open-source have been documented in the literature, relatively little is known about how the social networks that open-source contributors form impact their chances of long-term engagement. In this paper we report on a mixed-methods empirical study of the role of social capital (*i.e.*, the resources people can gain from their social connections) for sustained participation by women and men in open-source GitHub projects. After combining survival analysis on a large, longitudinal data set with insights derived from a user survey, we confirm that while social capital is beneficial for prolonged engagement for both genders, women are at disadvantage in teams lacking diversity in expertise.*

3.1 Introduction

Sustained participation by contributors in open source software (OSS) is critical to the survival of OSS projects [160, 9], and it can provide many benefits to individual contributors [110]. For example, a recent survey [14] found that OSS work helped more than half of the respondents obtain their current positions, and that OSS work in general helps people build their professional reputation. Given the advantage that open source experience can bring to an individual and the benefit that sustained participation can provide to OSS projects, it is essential to study what retains or repels contributors.

Not surprisingly, sustained participation in OSS has attracted considerable attention among researchers, with prior work focusing on developers' motivation [160, 161, 94], the kind of tasks they perform [162, 163] , and rejection experiences [164, 165, 166, 167, 168].

However, the benefits that contributors can gain from their OSS social relations and structures have not been studied. Such benefits are known in the social sciences as *social capital* [169, 170]. Social capital can be built through individuals' social networks and has been shown to affect various kinds of human endeavors, from knowledge sharing [171] to labor force participation [172] and from philanthropy [173] to financial development [174].

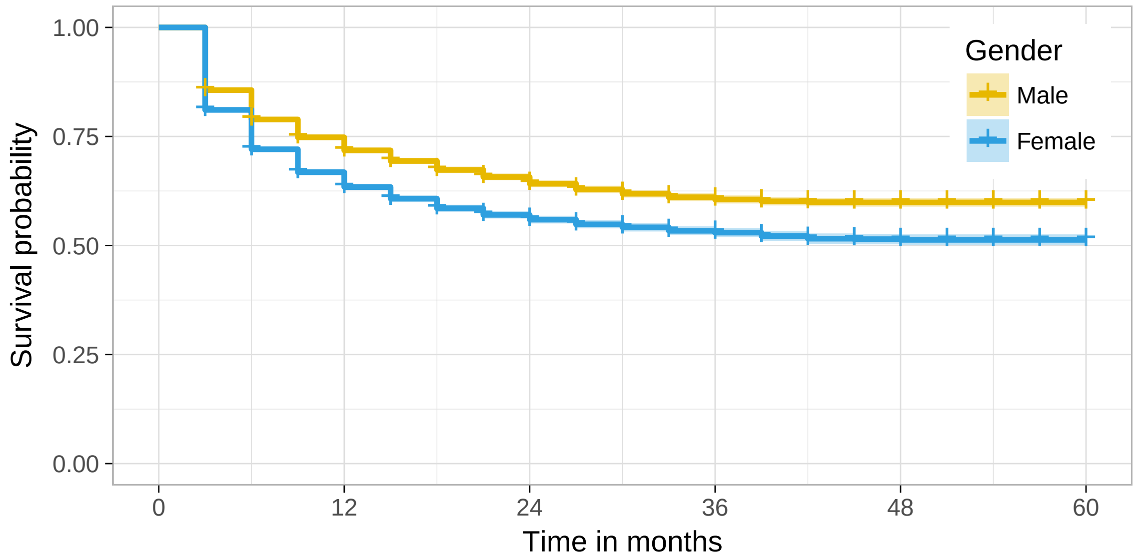


Figure 3.1: Kaplan-Meier estimators: women disengage significantly earlier. (chi-sq= 645, p< $2e^{-16}$ per a log-rank test)

In OSS, studies have shown that prior social ties can influence forming or joining a new team [175, 176]. However, they did not explore whether and how social ties can prolong contributors' participation.

While social capital can be built and leveraged by everyone, it can impact women differently in male-dominated environments. For example, prior work in the film industry [177] found that while men benefit from strongly connected networks, women do not; moreover, women benefit from diversity in teams and tasks. In OSS, women are severely underrepresented and, as we show, likely to disengage from GitHub participation earlier than men (Figure 3.1).

To better understand contributors' disengagement, we perform a longitudinal, quantitative analysis of the structure of OSS contributors' social networks on GitHub and the impact of this structure on prolonged engagement, through the lens of social capital theory. Moreover we report on a user survey to better understand what constitutes social capital for GitHub open source contributors and how it is associated with their participation sustainability. Our findings highlight that:

- Contributing to projects where team members are more familiar with each other (from prior collaborations) is in general associated with decreased risk of disengagement;
- Women are at higher risk of disengagement than men.
- Higher team diversity along dimensions of programming language expertise is associated with a decreased risk of both short and long term disengagement. *Moreover*, gender and language diversity interact: when team members have more diverse programming language backgrounds, women are less likely than men to disengage early.

Our results have implications for project choosing, team formation, and project management in OSS. Based on our results, we especially recommend that women take project social capital and expertise diversity into consideration when choosing a project to join, and that project managers consider these aspects when allocating developers to tasks, in more centrally managed contexts. We also argue that social coding platforms like GitHub could benefit from recommendation engines for newcomers looking for projects to join; these should take social capital into account when making a recommendation (cf. [178]); furthermore, GitHub could facilitate project maintainers tracking trends in factors negatively associated with the development of social capital, particularly among women.

3.2 Development of Hypotheses

We build on *social capital theory*, a popular social sciences theory used to explain individual and group success and performance (for an overview see Adler and Kwon [179]). *Social capital* is the set of benefits individuals can gain from their social connections and social structures, such as access to information and emotional support [179]; it is a complement to human capital, which refers to an individual's ability [170].

OSS is a social environment that can be modeled as collaborative social networks [180], where social capital can form: projects are community-based in nature; contributors have ample opportunities to connect with each other by interacting and collaborating over time; they agree on common norms; and they share collective goals—the development and maintenance of OSS. Once present, social capital can "make individuals' experiences of working on open source projects both satisfying and rewarding" [181]. In this paper we argue that *social capital also impacts the overall open source tenure of contributors*, and that female and male contributors benefit from social capital differently, on average.

There are two main network structures conducive of social capital: strong, dense, and cohesive ties generate *bonding social capital* [182], while weakly connected ties, acting as brokers between subgroups, generate *bridging social capital* [170].

The first, *bonding social capital*, emerges from *network closure*, *i.e.*, strongly connected ties [182]. Tie strength increases with the amount of interaction between individuals, emotional density, intimacy, or reciprocal service [183]. In a closed network, information is passed more accurately through direct communication [184], and trust develops more easily since it is more expensive for people to break norms when actions are more easily noticed [182]. At the same time, network closure increases group cohesiveness and solidarity among group members, who become more likely to remain engaged.

In OSS, contributors are motivated by both intrinsic and extrinsic factors, among which aspects related to bonding social capital, such as identifying with the community and feeling obligated to contribute back, are highly important [94]. Prior work showed how identification, obligation, emotional attachment, trust relationships, and shared goals and norms (all of which are more likely to develop in cohesive teams [185]) positively impact individual and team outcomes. It follows that bonding social capital should positively impact the contributors' willingness to sustain their OSS activity. In OSS participants are often free to disengage at any time, therefore the extent to which they have a sense of social identity, or perceive themselves to be part of the community, may substantially increase their intention to continue [186, 187].

In contrast to bonding social capital, *bridging social capital* focuses on how network individuals who maintain weak ties can benefit from a brokerage position [170]. In closed networks people who are strongly connected may have the same information or the same source of information. Bridging otherwise disconnected groups, what Burt calls structural holes [170], can enable access to broader sources of information and improve the information's quality, relevance, and timeliness [179]. While bridging social capital is especially beneficial in competitive scenarios, when timely and non-redundant information about job opportunities can be an advantage, it can also be an asset in OSS. Weak ties can expose contributors to, *e.g.*, new technologies and new projects, providing opportunities to continue their engagement. Already, evidence suggests that past collaborative ties impact contributors' choice of OSS projects to participate in [176]. Network brokers can also decrease the centralization of OSS communities and increase communication between experts and peripheral users [188].

To summarize, network closure and structural holes, representing both types of social capital, seem important for sustained participation in open source. We expect that:

$\mathbf{H}_1$. *During their open source tenure, the more often people participate in projects with high potential for building social capital, the higher their chance of prolonged engagement.*

However, network closure may not always be beneficial. As Lutter [177] notes "cohesive networks might foster discrimination and exclusion, as network closure is likely to divide [individuals] into insiders and outsiders". Outsiders, *i.e.*, those who are not part of the "core" group, can have a harder time accessing information, leading them to miss out on some chances [189, 190, 169]. Furthermore, people within a social group tend to develop their own habitus, often unconsciously. Such habitus embodies membership but also restricts outsiders from accessing and identifying with the group [191, 192, 193].

In OSS in general and GitHub in particular, socio-demographic diversity is lower than anywhere else in tech [194]. Women are particularly underrepresented, with recent surveys placing them at less than 5% [195]; women are also more likely than men to encounter stereotyping or unwelcoming language [5, 58, 7]. However, as prior results from the film industry, a similarly male-dominated field, show, women can overcome the negative effects of network closure: being more often attached to open teams with regard to diversity of ties, information flow, and genre background increases chances of career survival [177]. That is, since women tend to be outsiders to the strongly connected groups of (mostly male) decision-makers, diversifying their ties makes them less dependent on the in-group for acceptance [196]. Therefore, given women's minority (and likely outsider) status in OSS in aggregate, we expect:

$\mathbf{H}_2$. *During their open source tenure, the more often women participate in open teams wrt diversity of ties and information, the higher their chance of prolonged engagement.*

3.3 Related work

Discrimination exists in online software engineering communities and women are known to face greater barriers than men [197]. Terrell *et al.* show that women whose gender identities are revealed have lower pull request acceptance rate [7]. Mendez *et al.* have observed biases against women in GitHub tools and infrastructure [178], while Ford *et al.* identified barriers for female participation on Stack Overflow [198]. Social network analysis has also been applied to OSS [175, 176, 180, 199, 200, 201, 202, 203], although these studies did not consider gender.

Sustained participation, turnover and disengagement have attracted significant attention as well, *e.g.*, using qualitative methods, Fang *et al.* reveal that situated learning and identity construction are associated with sustained participation [160], while Lin *et al.* show that contributors who join the project earlier, write code instead of documents, or are responsible for modifying code have higher chances of remaining in the team [162]. The relation between turnover and project quality has been studied by Foucault *et al.* [101]. A complementary perspective has been taken by Zhou and Mockus that identified metrics such as number of comments and the size of the peers' groups as characteristics of new contributors that will become long-term contributors [204]. These conclusions, however, focused on individual behaviors and project qualities. In this paper, we analyze sustained participation from the perspective of contributors' social connections on GitHub.

3.4 Methods

We designed a mixed-methods study characterized by a concurrent triangulation strategy [126] to help triangulate our findings. Quantitatively, we collected a multivariate longitudinal data of 58,091 GitHub contributors, and performed survival analysis to model the effects of social capital on disengagement. Qualitatively, we surveyed a sample of 88 contributors to gain additional insights into the role of social capital on GitHub.

3.4.1 Data

Our main data source is the February 2017 version of GHTorrent [205], a publicly available historical database of GitHub public activity traces, containing data for approximately 16M users. Gender is not recorded in GitHub profiles and, consequently, is also not available in GHTorrent. Therefore, we inferred it from people's names, as described in Section 3.4.2, and augmented the GHTorrent data. However, since social network analysis on a data set of GitHub's size would be computationally unfeasible, we first compiled a smaller sample of 58,091 users, as follows.

Preprocessing and Filtering Starting from the $\sim$ 16M users in GHTorrent, we filtered out organizational users (*i.e.*, metausers, not usually corresponding to a single person), users with deleted accounts, users who never authored any commits and users with names not containing any space (gender inference techniques rely on a person's first and last names; *e.g.*, Alice would be excluded, but Alice Smith and Alice Marie Smith would not). We acknowledge that some cultures do not split names into parts, or some people are known mononymously. We chose this conservative heuristic, which excludes some valid names, since we noticed during manual exploration of the data that many single-part names are English words or nicknames from which we cannot extract gender information. Approximately 1.8M GitHub users in our data had non-organizational, non-deleted accounts, authored at least one commit, and had names consisting of at least two parts.

Identity Merging Since git version control settings are set locally by each client, there are some cases where git commits are not attributed to the correct GitHub account, which introduces noise in the data. Moreover, the same contributor may have used different git "aliases" (*i.e.*, names and emails) in different projects or over time [206]. To have a more accurate representation of one's activity and contributions, we performed identity merging on the different (name, email) tuples in our data using a series of heuristics (cf. [206, 207, 208]).

Sampling After initial filtering and identity merging, we randomly sampled 300,000 users and applied our gender inference technique (Section 3.4.2) to label each account as Female

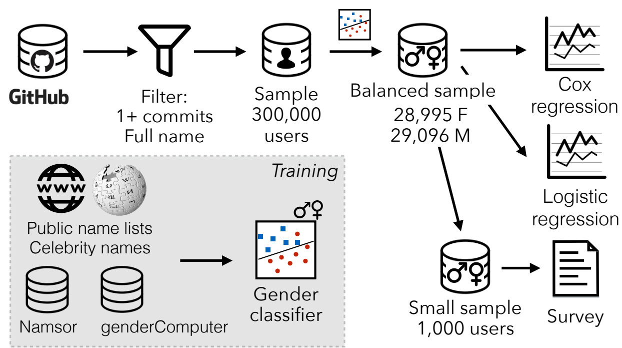


Figure 3.2: Overview of our methodology.

(9.7%), Male (84.85%), or Unknown (5.45%). Some of our social network analysis measures (Section 3.4.3) require, for every person, to collect all the repositories they contributed to, and for every repository, to collect all other contributors and all *their* repositories. To reduce computational effort and to address the Female–Male imbalance in our sample, we randomly down-sampled the group of male contributors to the same size as the female group. After removing users who have only contributed to educational projects, our final dataset contains 28,995 users labeled Female and 29,096 users labeled Male. Figure 3.2 gives an overview of our data collection process.

3.4.2 Gender Inference

Various approaches and tools for name-based gender inference have been proposed [209, 210]. All operate with the simplifying assumption that gender is binary; we also assume binary gender here to simplify data collection and analysis. We tried many of these tools and found that each has strengths and blind spots. In particular, most tools are based on databases of English names and as such fail, *e.g.*, on Asian names.

We have considered approaches that use social network data, specifically *Google+* [7], but the gender API has been deprecated; tools that can infer gender from photos, *e.g.*, *Face++*, but discarded these since GitHub profile photos are scarcely available; and tools that can infer gender from text [211], but discarded these since we have a very limited amount of text for each user – mostly commit messages, which are usually too short to provide enough information.

Instead, we identified two main contenders among tools that rely on broader datasets of names in different languages, and integrate them in a classifier (*i.e.*, a voting system). Our first contender is *genderComputer*[1] [212]. As opposed to other tools it uses location information to disambiguate; *e.g.*, it is able to distinguish between Italian Andrea (predominantly male) and

[1] https://github.com/tue-mdse/genderComputer

Table 3.1: Accuracy of the different gender inference methods (bolded are the highest accuracy for that language).

Language	genderComputer (%)	NamSor (%)	Our classifier (%)
Chinese	17.58	6.70	**60.00**
Japanese	76.76	26.88	**79.71**
Korean	18.82	13.51	**68.07**
All	79.41	74.07	**83.62**

German Andrea (predominantly female). Our second contender is *NamSor*[2] which classifies personal names by gender, country of origin, and ethnicity, with good coverage of different languages, countries, and regions. We trained and tested a Naive Bayes classifier that takes as input the gender predictions output by *genderComputer* and *NamSor* for a given name as well as features of the name itself, and produces a gender label as output, *i.e.*, one of Female, Male, or Unknown.

As training (80%) and test (20%) data, we compiled a list of 11,706 names from two sources. First, we randomly sampled 8,706 names from *genderComputer*'s open source dataset, which covers 28 countries. Second, since both input gender tools often have difficulty with East Asian names, we further collected a total of 3,000 romanized Chinese, Japanese, and Korean names from celebrity name lists on Wikipedia, websites for baby names, or name lists found in online public datasets, *e.g.*, lists of recent school graduates or of enrolment.

For each name, we obtained the gender inferences from *NamSor* and *genderComputer*. We also extracted features from the name itself, including the last character (*e.g.*, in Spanish, names ending in 'a' tend to be female), the last two characters (*e.g.*, in Japan, names ending in 'ko' tend to be female), and tri-grams and 4-grams to capture romanized Chinese, Japanese, and Korean names. We also included *NamSor*'s inference on the contributors' countries of origin from their last names as a feature. Using the country of national origin inferred from last names, instead of the country of residence declared on the GitHub profile, is an improvement on prior work, because it can increase the gender inference accuracy for people residing outside their (or their ancestors') country of origin, *e.g.*, Italian Andrea's living in the US. We note, however, that this approach can still fail in some cases, *e.g.*, for a person with a Chinese last name and a non-Chinese first name such as Andrea Zhang.

Table 3.1 reports the accuracy of the gender inference tools and our classifier overall as well as on names in East Asian languages, which are typically the hardest to make inferences on [210]. Overall, our combination classifier has higher accuracy on all categories of names than either *genderComputer* or *NamSor*. Our classifier fails mostly on gender neutral names, such as Robin and a Chinese name Yan that can be both male and female, depending on what Chinese character it is associated with. We also do not have enough training samples to make accurate inference from languages such as Burmese.

3.4.3 Operationalizations of Concepts

To model the effects of different dimensions of social capital on sustained participation on GitHub, our statistical modeling technique (survival analysis, Section 3.4.4) involves

[2] http://www.namsor.com

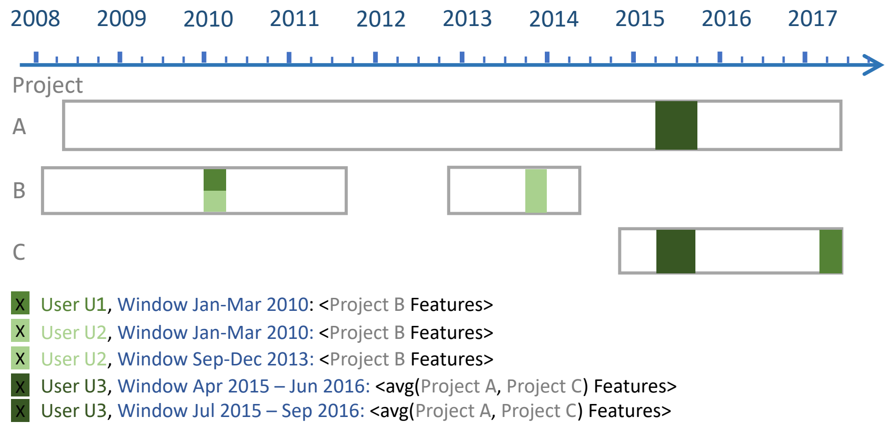


Figure 3.3: Illustration of data points we collect.

operationalizations of the different theoretical concepts discussed in Section 3.2. We introduce the following operationalizations.

Panel Data An implicit assumption for social capital effects to manifest is that project members had a chance to interact with each other. Since GitHub projects can be long-lived and since open-source projects in general face high turnover [162, 101], we assemble a longitudinal panel data set with measures computed over shorter time intervals; specifically, we aggregate all data from 2008 to 2016 into consecutive three-month windows, *i.e.*, we compute quarterly values for all measures.

Note that this involves two levels of aggregation. First, for every person and every project they contributed to, we compute quarterly values for different project-level measures (details below). Second, whenever someone contributed to more than one project in the same three-month window, thus having different sets of values for different projects in that window, we average out their project-level measures across their different projects that window; our results are qualitatively similar (significance and directionality of regression coefficients) if we compute the maximum instead of the average across projects. Figure 3.3 illustrates the structure of our data.

GitHub Disengagement—Outcome Variable The dependent variable in our model is the occurrence of the disengagement event: *i.e.*, if every commit a person authors is an indication of repeated engagement, we consider a person's last recorded commit as an indication of disengagement if "long enough" time has elapsed for potential subsequent commits to be observable. Naturally, programmers may take a break from GitHub and return later for more contributions. Moreover, one's last recorded commit may be very close to the end of the observation period, so it is not clear whether they will return to contribute more; this common phenomenon in longitudinal data is known as right censorship (the disengagement event did not happen during the course of study) [213].

We considered 12 months of inactivity as "long enough" to confidently detect disengagement, and used this operationalization in our survival models. Specifically, we consider that a GitHub contributor has disengaged at time t if they have not committed anything to any open-source project for 12 months after t; *i.e.*, the *has_disengaged* value is 1 in the three-month window containing t, and 0 in all previous windows. Consequently, we also consider that people whose last recorded commit is less than 12 months prior to the end of our data are still active. Our models are robust to this operationalization and the results are qualitatively similar (significance and directionality of regression coefficients) with 6 months instead of 12. Note that we excluded 9,269 people with 12 months or more of inactivity that returned to make new contributions. Among them, 4,932 were male, 4,337 female.

Team Cohesion Measures $\mathbf{H}_1$ assumes that during their open-source tenure, the more often GitHub contributors participate in projects with high potential for building social capital, the higher their chance of prolonged engagement, *i.e.*, strongly connected networks and presence of ties between subgroups increase the likelihood of sustained participation in open-source. While subgroup or community detection has been extensively studied in the social network analysis literature [203], as argued by de Vaan *et al.* [214] these techniques are not suited for the operationalization of social capital constructs. Indeed, community detection techniques interpret ties as a static construct, while interpersonal relations, trust, and the implied social capital develop in time. Hence, to argue presence of a tie between two developers, the relationship between them should be durable, and this durability should be reflected in the operationalization. Therefore, as operationalizations for ties in team structures, we follow Lutter [177] and de Vaan *et al.* [214] and compute two distinct but related measures of social capital: interpersonal team familiarity and team recurring cohesion.

Team Familiarity We adapt Newman's [215] measure of average interpersonal familiarity within a team, which captures the intensity of prior collaborations between each pair of current team members; the measure of strength of a developer's social connection to a project by Casalnuovo *et al.* [176] is conceptually similar. Team familiarity is aggregated over pairs of contributors (dyads), and as such it is capable of capturing both ties within subgroups and between subgroups, corresponding to bonding and bridging social capital.

To calculate dyadic interpersonal familiarity for project p in time window t, we iterate over all time windows prior to t. Let i and j be two contributors to project p and let and r_{is} and r_{js} be the sets of projects they worked on in time window s, respectively. The familiarity between i and j at time t is defined as the number of projects they worked on together in past windows $s < t$, adjusted by the team size of each project at that time, assuming that people who work in a smaller team are more familiar with each other. Only collaborative projects ($|r_s| > 1$) are considered. Then, the values of each window s are summed to result in the interpersonal familiarity measure w_{ijt} defined as

$$\sum_{s=1}^{t-1} \sum_{r_s \in (r_{is} \cap r_{js}), |r_s|>1} \frac{1}{|r_s| - 1}$$

.

To measure team familiarity for project p in time window t, we define Team familiarity$_{pt}$ as the sum of w_{ijt} for all pairs of contributors i and j normalized by the number of pairs of contributors to p in time window t: The values range from 0 to 299.0.

Recurring Cohesion To capture tendencies for possible network closure from team cohesion, we again follow Lutter [177] and de Vaan et al [214] in calculating a measure of recurring cohesion, which captures cliques of at least three people who have previously worked together. If three programmers have worked on some project before, and they later worked together again, the network containing this three-person clique can be considered more cohesive than that where any three people only share dyadic ties. A clique is defined as a group of people who at some time prior to current window t worked on a common project within a three-month window; to reduce the complexity of enumerating and checking all possible cliques of large teams, we only consider cliques of up to five members.

After identifying all q_p cliques for a project p at time t, we construct a $q_p \times q_p$ matrix $\mathbf{M}^p$, where each entry (v, w) contains the number of people shared by cliques v and w. Then we use all the off-diagonal, lower triangular values of $\mathbf{M}^p_{v,w}$ to calculate the recurring cohesion as:

$$\text{Recurring cohesion}_{pt} = \frac{1}{2(q_{pt}-1)} \sum_{v<w \wedge v,w \in p_t} \frac{|v| + |v \cap w|}{|p_t|}$$

If there are no cliques, this measure is assigned 0; if there is exactly one clique, say v, the measure is calculated as $\frac{|v|}{|p_t|}$. The values range between 0 and 1547.5.

Team Diversity Measures H$_2$ tests whether attachment of women to open teams with regard to diversity of ties and information increases their chance of prolonged engagement relative to men's. To operationalize diversity of information we compute the share of newcomers and heterogeneity of programming language expertise. Indeed, the more newcomers are in a team, and the more diverse expertise team members have, the more diverse is information exchanged in the team.

Share of Newcomers Following Lutter [177] and Perretti and Negro [216], we calculated each team's share of newcomers, *i.e.*, the fraction of newcomers in a project in time window t relative to the size of the project team at time t. The more newcomers there are in a team, the more new ideas can be brought in, and the more new combinations of relationships can be formed. We operationalize newcomers at project level, *i.e.*, people who never contributed to a given project prior to time t.

Heterogeneity of Programming Language Expertise Prior work has shown that diverse knowledge is important to innovation and sustainable competitive advantage in many domains [217]. A similar effect may be visible in OSS teams, where assembling a diverse team with expertise in different programming languages or technologies may provide a competitive advantage, and may help create social connections between members that bridge communities and create opportunities.

Following Lutter's measure of genre diversity in the film industry, based on the distance measure of de Vaan *et al.* [214], we calculate a measure of programming language background heterogeneity at project team level, that considers each team member's prior experience with different programming languages from prior open-source GitHub projects. We begin with a list of the most popular 33 languages on GitHub [218]; all other languages in our data are labeled 'Other', generating a set of $K = 34$ languages. On GitHub each project is labeled with the predominant programming language used therein. Given a project p labeled with the predominant language k, we consider that all developers who contributed to p have experience with k: while individuals may vary in their experience with k, given the size of the dataset we expect a reduction to the mean in terms of individual knowledge; *i.e.*, we expect that, on average, project contributors would have had experience in the predominant language.

For each contributor i in project p in the current time window t, we calculate the vector $f_i = (f_{i1}, ..., f_{iK})$ for each language k, where f_{ik} is 1 if i has worked in projects labeled with the predominant language k. Then, the programming language background distance d_{ijt} between two contributors i and j in the time window t is defined as the cosine of their respective experience vectors. Possible values for this measure range from 1, indicating complete similarity in the language histories of i and j, to 0, indicating complete dissimilarity. Future refinements to this measure, beyond the scope of the current paper, could also consider how similar different programming languages are with each other [219]. We then aggregate these similarity measures at project level, over all pairs of contributors i and j, $i > j$, adjusted for team size, and subtract the result from 1 to obtain a degree of dissimilarity:

$$\text{Language heterogeneity}_{pt} = 1 - \frac{1}{\binom{|p_t|}{2}} \sum_{i>j \wedge i,j \in p_t} d_{ijt},$$

Control Variables As control variables we consider:

Is Project Owner and *Is Project Major Contributor* both control for the contributor's position in the project. We define major contributors as those authored at least 5% of the project commits during a given window [220]. Being a repository owner or major contributor indicates higher levels of commitment, hence, we expect differences in disengagement rates.

Number of Followers and *Number of Repository Stars* both control for visibility of the contributors and projects, respectively [121]. Popular developers, or developers contributing to popular projects, tend to have a different experience on GitHub and may be less likely to disengage [26, 97].

Niche width, *i.e.*, the number of programming languages of the developer's past GitHub commits are spread across. We expect individuals knowing multiple languages to be more versatile and less likely to disengage.

3.4.4 Survival Analysis (Quantitative)

To test our hypotheses quantitatively, we use survival analysis, a statistical modeling technique that specializes in time to event data [213]. Survival analysis is particularly suitable for modeling right-censored data like ours.

Estimation We model jointly the effects of the different social capital factors in Section 3.4.3 on the time to the GitHub disengagement event, while controling for covariates. For each GitHub developer in our sample, we have a *survival time* T on record (number of quarters until *has_disengaged* becomes 1). The probability of reaching a given survival time t is given by the *survival function* $S(t) = P(T > t)$, and the probability of leaving the state at time t is given by the *hazard rate* $h(t) = \frac{P(T<t+\Delta t|T\geq t)}{\Delta t}$. The Cox model is a non-parametric regression which can estimate, using partial likelihood, the effect of some independent variables X on the hazard rate, $h(t, X) = \theta(t)f(X)$; *i.e.*, it can estimate the coefficients β of the regression $h(t, X) = \theta(t)\exp(\beta' X)$, where β' denotes the vector transpose of β [213]. The coefficients β can be directly interpreted, *e.g.*, if $\beta_i = 2$, then a unit increase in X_i decreases the probability of survival by $\exp(2) = 7.4$ times.

Many developers disengage early, in their first quarter. In open-source, occasional contributions [221] are common. To model how the different factors contribute to explaining the variability in disengagement rates differently early compared to later on, we split the data set into two parts: developers who disengage in the first quarter and the rest. Since the former only contribute one observation each (one quarter), we model this group using logistic regression (`glm` in R). For the remaining developers, the data set contains repeated quarterly observations. To model these, we estimate a Cox proportional-hazards model.

Diagnostics Whenever variables had highly skewed distributions, we removed the top 1% of values as potential high-leverage outliers, to increase model robustness [222]; we also log-transformed variables, as needed, to reduce heteroscedasticity [135]. We then tested for multicollinearity (and removed predictors, as needed) using the variance inflation factor (VIF), comparing to the recommended maximum of 5 [136]. Next we inspected the Schoenfeld residual plots [223] (graphical diagnostics) to test the assumption of constant hazard ratios over time. Finally, we report p-values for model coefficients as well as estimates of their effect sizes (fraction of variance explained) from ANOVA analyses.

3.4.5 Developer Survey (Qualitative)

To better understand how social capital might impact women and men on GitHub differently, we conducted a user survey.

Survey design The aim of the survey was to gain additional context information about how open source contributors perceive their respective projects and the way they collaborate in those project. The survey instrument thus focuses on contributors to collaborative open source GitHub projects (with at least three contributors, to exclude "toy" projects [128]). Respondents were instructed to choose such a project and base their answers on their experience therein.

We asked open ended questions focusing on their perceived responsibilities and (if applicable) reasons for them to stop contributing. Furthermore, we asked Likert scale questions covering individual satisfaction of contributors being part of this particular project [224], perceived work engagement [225], perceived social capital [226] (the principal construct of our study) and the frequency of communication using different means of communication. We opt to measure individual satisfaction since it has been repeatedly related to loyalty [227], and therefore more satisfied developers can be expected to be less likely to disengage; while work engagement has been shown to be related to turnover intentions [228]. We also aim to assess communication as additional context information about how open source contributors collaborate. For the first three scales we rely on existing instruments that we adapted for our context. In order to assess the frequency of communication we developed a scale that covers different potential means of communication such as *reading each other's code*, *text messaging*, *email* and others. This scale is divided into four levels ranging from *"never or hardly ever"* to *"every day or almost every day"*. The provided means of communication cover typical technologies, *e.g.*, text, audio/video messaging, and typical means of communication in OSS projects, *e.g.*, reading each other's code, commenting on existing code. We also included in person communication for co-located teams.

We also included multiple questions that focus on individual programming skills. The purpose of these questions is not only to assess the potential bandwidth of different skill levels. It can also be expected that differences related to skill level can have an impact on the social structure within a project. Similarly to the niche width in the repository data analysis, we asked participants to identify programming languages that they feel comfortable using. The list we used was based on the most commonly used programming languages in GitHub. We also asked contributors for how many years they have been active in OSS projects in general and how they rate their skills in comparison to their fellow project contributors. This question has been found to be mostly related to actual programming experience by Siegmund *et al.* [229]. The latter question is related to the tenure diversity shown to be a predictor for turnover in GitHub teams [58]. Finally we included typical demographic questions: the age and gender of the participants and their education level. Wang and Fesenmaier have shown that when keeping age and educational level constant, men have been members of an online community for a longer period of time [230]. The educational level was based on the Educational Attainment scale by the United States Census Bureau.

Procedure The population of interest for our study includes female and male contributors to open source GitHub projects with at least 3 members. We piloted the survey internally with 3 individuals and externally by contacting a total of 800 individuals (400 identified as female and 400 as male by the gender prediction algorithm). Based on the 43 responses we received (5.38% response rate), we revised the survey instrument. For the final survey, we sent 500 invitations to contributors identified by the gender prediction algorithm as women and 500 invitations to those identified as men. The delivery of 6 invitations failed. The survey was available for 2 weeks. We received 107 responses, for a response rate of 10.7%. Responses were anonymous and participation was voluntary. Out of the 107 survey responses received, 93 were complete. Out of the complete responses, 32 respondents identified as female, 56 as male, and 5 did not disclose their gender, which leaves 88 usable responses for the following analysis.

The average reported GitHub tenure of our survey respondents was 2.50 years, slightly less than what other studies found (*e.g.*, [197] found an average of 3.07 years). This difference could be explained by the larger share of female participants in our survey (36% as opposed to 25% in the survey by Vasilescu et al. [197]) and the fact that female participants in general report shorter tenures than male participants. The tenure of our survey participants is thus generally comparable to that of others in a similar setting. For open ended questions, we conducted an open coding procedure (one author, expert qualitative researcher). For perceived responsibilities we referred to the contributor types that can be found in the GitHub open source survey [195]. For potential reasons to discontinue contributing to an OSS project we reversed the motivations to contribute to open source [22]. The categories were iteratively refined.

Accuracy of gender prediction We found a strong correlation between the computed and reported gender. Out of the 107 responses we received, a total of 53 were responses to the survey that we sent to contributors that were identified by the algorithm as female and 54 were responses that were identified by the algorithm as male. Out of the 54 participants our algorithm identified as male, 52 identified themselves as male in the survey and 2 elected not to disclose their gender. Out of the 53 participants our algorithm identified as female, 37 identified themselves as female, 13 identified as male and 3 elected not to disclose their gender.

The algorithm was thus nearly perfect in terms of predicting whether or not a contributor indeed is of male gender (96.30%), as expected given that males are the majority group. The accuracy for predicting whether or not a contributor is of female gender was lower (69.81%) but still above chance. Our algorithm also did not classify female as male contributors: indeed, all participants that were classified as male either reported to be male or did not disclose their gender. This also suggests that the probability of the algorithm missing the contributions of women should be low, since it is capable of detecting male contributors with high accuracy (cf. [209] for discussion of the importance of not misclassifying women).

3.4.6 Replication Package

Our data collection and data analysis scripts, the survey instrument, and the input data for the regression models in Table 3.3, are part of a replication package.[3]

3.5 Results

3.5.1 Survey results

What responsibilities do survey respondents have? We asked participants about what they perceive to be their overall responsibilities in the project they selected. To analyze the answers we conducted an open coding procedure based on on the different contributor types in the GitHub open source survey.[4] While applying the contributor types to the survey responses we discovered additional codes ending up with nine distinct but not mutually exclusive responsibility categories.

While participants reported anything between no responsibilities at all and five different responsibilities, most participants reported either one or two. For both genders contributing code is by far the most common perceived responsibility (76.14%), with project management (30.68%) and project lead (22.73%) following at a distance. Male contributors mainly perceive themselves as leaders or managers (37.50% of males report those as their perceived responsibilities) while females appear to take over more non-code related activities such as documentation and proposing ideas (62.50% of females report those as their perceived responsibilities). While this observation concurs with the higher participation of males in the mailing lists related to designing technology [212], the difference is not statistically significant ($p = .869$ for non-code related activities).

How do survey respondents communicate? We analyzed whether and how respondents interact with each other based on different means of communication. We found that 10 out of 88 respondents never communicated with their fellow project members; Eight of those identified as male (9.09%) and two as female (2.27%). Most of our survey participants thus communicated via any of the provided means of communication.

[3] https://doi.org/10.5281/zenodo.2550931

[4] https://github.com/github/opensource-survey/blob/master/survey-instrument.md

Participants most commonly communicated via text messages, comments on code and reading each others code in general (almost half of respondents communicate in this way at least once or twice a week). Mail and in person communication are less popular (35.23% and 28.41%, respectively) followed by social networks (11.36%), video messaging (15.91%) and audio messaging (20.45%). Although there are no statistically significant differences between female and male contributors in terms of their communication behavior ($p = .979$), a closer look into the respective frequencies reveals that female contributors are slightly more active communicating with their fellow project members. This observation concurs with the results of Razavian and Lago: their study has shown that communication is seen by software architects as feminine expertise [231]. In particular, women use text and audio messages as well as social networks more frequently. Males on the other hand appear to use comments on code more frequently than females.

How experienced are the survey respondents? We also asked survey participants about their age, educational background and experience related to both programming in general and contributing to open source projects in particular.

The respondents were mostly between 18 and 34 years old (56.8%) and have a bachelor's or master's degree (67.0%). They reported feeling comfortable using between two and six of the proposed programming languages (77.3%; niche width). Comparing female and male contributors we found that male contributors reported a significantly higher number of programming languages they feel comfortable using ($F = 6.646$, $p < .05$, $\eta^2 = 0.072$). We also found males to report a significantly higher level of expertise ($F = 5.643$, $p < .05$, $\eta^2 = 0.062$). Both are medium effects as demonstrated by η^2 values [232]. There were however no significant differences between female and male contributors in terms of reported age, level of education and years of experience in open source projects. One explanation could be that female contributors are less confident about their programming expertise than male contributors, while neither their education level nor their experience in contributing to open source suggest a valid reason for this perceived difference. This would concur with Wang *et al.*'s finding on women's confidence-competence gap [233].

Why do people stop contributing to GitHub projects? Most of our survey participants are still active in open source (73.9%). Out of the 32 respondents who identified as female, 6 reported that they stopped contributing to open source, while 26 reported that they are still active. Among males, out of the 56 respondents, 17 reported that they stopped contributing while 39 reported that they are still active.

We then conducted a logistic regression analysis on the survey data, using data from the different scales, to model the factors that explain and predict disengagement (binary variable). The multi-item scales we used (individual satisfaction, perceived work engagement, and perceived social capital) are all reliable (Cronbach's α between 0.84 and 0.92). We built an explanatory model, including data from the three scales above, as well as programming experience and reported gender as independent variables. Results from this regression analysis (Table 3.2) showed that **perceived bridging social capital** and **years of programming experience** are significant predictors of individual disengagement. Both bridging social capital and years of experience are comparably strong predictors for individual disengagement (cf. deviance explained in Table 3.2). Gender had no significant direct influence on disengagement.

Table 3.2: Regression model for the user survey data ($N = 88$).

	GitHub disengagement response: *has_disengaged = 1* exp(Coeffs) (Err.)	LR Chisq
(Intercept)	14.41 (2.55)	
Individual satisfaction (Avg)	2.23 (0.52)	2.95
Work engagement (Avg)	2.00 (0.38)	3.97*
Bridging social capital (Avg)	0.22 (0.60)*	8.37**
Bonding social capital (Avg)	0.61 (0.34)	2.18
Experience relative to team	0.74 (0.31)	0.91
Years of experience	0.72 (0.14)*	6.87**
Education	0.77 (0.24)	1.27
Self-reported gender	2.83 (0.69)	2.44
Niche width	0.96 (0.17)	0.06

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

When looking into self-reported reasons for discontinuing to participate in a GitHub open source project, we found two main reasons: (1) not having enough time to contribute anymore; and (2) no immediate personal need for the respective project. Lack of time was reported to be caused by work related (*"changes in job"*, *"work became over bearing"*) as well as personal reasons (*"diversifying hobbies"*, *"personal life"*). Lack of time was also identified by Lee *et al.* as the most common barrier to participation faced by one-time-contributors to FLOSS projects [234]. Other reported reasons were *"the end of funding of our project"*, frustration (*"failure of our team of backend and front-end"*) or the perception that *"the project [...] is finished"*. When comparing reasons to disengage we found female contributors to report personal reasons significantly more often (F = 4.87, p < .05, $\eta^2 = 0.188$). This is a large effect, concurring with the higher likelihood of women leaving and reentering the labor force for personal reasons [235].

3.5.2 Survival analysis results

Who are the GitHub data developers? Out of 58,091 programmers, 39,643 have taken a break longer than half a year, and 25,196 programmers have taken a break longer than 1 year.

The average age of an account (number of months since the first commit) is 15.01 months; women are statistically younger than men ($p < 2.2^{-16}$, Cliff's $\delta = 0.23$) these results concur with our survey and earlier observations [236, 197]. On average, a programmer contributes to 9.55 projects (median = 4); statistically, women contribute to fewer projects than men ($p < 2.2^{-16}$, Cliff's $\delta = 0.16$). The effect size is in both cases are small (< 0.33) [237].

How does social capital associate with disengagement? Figure 3.1 plots the Kaplan-Meier estimates revealing that contributors are most likely to drop out in the first two years,

Table 3.3: Regression models for early-stage disengagement ($N = 29,235$ users; $140,441$ data rows) and later-stage disengagement ($N = 26,299$ users; $143,984$ data rows).

	Early-stage (GLM) response: *Disengaged = 1*		**Later-stage (Cox)** response: *Disengaged = 1*	
	Coeffs (Err.)	LR Chisq	Coeffs (Err.)	LR Chisq
(Intercept)	1.61 (0.07)***			
Followers	0.61 (0.02)***	990.53***	0.70 (0.02)***	394.39***
Stars	0.89 (0.02)***	45.18***	0.86 (0.02)***	103.26***
Commits to date	0.63 (0.01)***	1635.38***	0.64 (0.02)***	718.15***
Is major contrib.	0.77 (0.05)***	29.05***	0.63 (0.06)***	62.96***
Is repo owner	0.56 (0.03)***	363.80***	0.51 (0.04)***	310.35***
Niche width	0.47 (0.05)***	244.20***	0.54 (0.05)***	132.70***
Is female	1.27 (0.03)***	68.79***	1.32 (0.04)***	59.96***
Team familiarity	0.84 (0.08)*	4.83*	0.79 (0.09)**	13.22***
Rec. cohesion	0.85 (0.04)***	30.77***	0.86 (0.04)***	28.46***
Share newcomers	1.07 (0.04)	3.37	0.78 (0.04)***	35.70***
Lang. heterogen.	0.70 (0.11)**	44.44***	0.63 (0.14)***	44.43***
Lang. heter.:Female	0.73 (0.15)*	4.36*	0.69 (0.18)*	4.30*
Female:Team fam.	1.09 (0.11)		1.05 (0.17)	
Female:Cohesion	1.02 (0.05)		1.01 (0.04)	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

and women are more likely to drop out than men in general. Table 3.3 presents summaries of our regression models: a logistic regression for contributors who disengage within their first three months of activity (left), and a Cox regression for contributors who disengage later (right).

In both models the control variables behave as expected. More popular (*i.e.*, followers), active (*i.e.*, commits to date) and versatile (*i.e.*, niche width) developers are less likely to disengage. Similarly, project owners, major contributors and contributors to highly starred projects are less likely to disengage. Moreover, as expected, female contributors are at higher risk of disengagement than males: in the short term, being female increases the odds of disengagement from GitHub by 27%; in the long term, by 32%.

The two variables related to team cohesion have statistically significant effects, and these effects are consistent between the two models. Contributing to projects where team members are more familiar pairwise with each other from prior collaborations (Team familiarity), or projects where cliques of three or more developers recur from prior projects (Recurring cohesion), is associated with decreased risk of disengagement.

The variables related to team diversity also have statistically significant effects. Heterogeneity in the programming language backgrounds of project team members is associated with decreased risk of disengagement both short and long term. Moreover, language heterogeneity has a statistically significant interaction with gender: women are more likely to disengage when language heterogeneity is low. Contributing to projects with high turnover (Share of newcomers) is associated with higher risk of disengagement after the first three months.

3.6 Discussion

3.6.1 Hypotheses

$\mathbf{H}_1$ linked social capital to the duration of engagement of OSS developers. Both aspects related to bonding social capital, such as the need to reciprocate, and those related to bridging social capital, such as exposure to new technologies and ideas can be related to developers' motivation. Therefore, $\mathbf{H}_1$ stated that the more often people participate in projects with high potential for building social capital, the higher their chance of prolonged engagement. Our study **strongly supports** this hypothesis. Both regression models (Tables 3.2 and 3.3) indicate that social capital, measured by an established survey measurement instrument [226] and by team familiarity and recurring cohesion metrics respectively, is a statistically significant predictor for disengagement. The regression coefficients are lower than one, meaning that *the increase in social capital decreases the chance of disengagement*, other variables held fixed.

$\mathbf{H}_2$ stated that attachment of women to open teams with regard to diversity of ties and information increases their chance of prolonged engagement relative to men's. Table 3.3 shows that $\mathbf{H}_2$ is **partially supported**. On the one hand, we found evidence that attachment of women to open teams with regard to diversity of information (language heterogeneity) increases their chance of prolonged engagement: language heterogeneity interacts with gender. On the other hand, no such interaction could be found for diversity of ties (recurring cohesion and team familiarity), therefore we conclude the support is only partial.

3.6.2 Implications

Our results provide empirical evidence that social capital impacts the prolonged engagement of contributors to open-source. Hence, researchers can consider social capital as a lens to investigate social phenomena in OSS.

Given the importance of and concerns about the sustainability of OSS [238, 10], our results suggest that social coding environments like GitHub should be redesigned to support women in developing social capital, on the one hand, and project maintainers in tracking and being able to react to factors that negatively impact the formation of social capital, on the other hand. We envision: 1) better search functionality and recommendation engines for newcomers looking for projects to join, that take the target project team cohesion and expertise diversity explicitly into account when making a recommendation, to facilitate the formation of social capital, in particular for women (cf. [178]); 2) stemming from the previous point, better mentorship support for newcomers in general and women in particular, whereby mentors can be automatically recommended to potential mentees to facilitate the formation of social capital (cf. [8]); and 3) UI elements besides the ones currently available on GitHub repository pages, such as badges [239], that allow project maintainers to track worrisome trends in factors negatively associated with the development of social capital (*e.g.*, team expertise diversity and turnover).

3.6.3 Threats to Validity

Like any empirical study, our work is subject to threats to validity. First, our results depend on the data collected by GHTorrent, which may not be a full replica of GitHub data [128]. We carefully cleaned and filtered our data to avoid the GitHub mining "perils" [128]. The project-level metrics are calculated based both on the contributors' own forks and their base repositories (the repository to which they make pull requests). We also focus on commits instead of pull requests because only a fraction of projects use pull requests [128]. We repeatedly manually checked data outliers *e.g.*, large repositories that are not software projects, but tutorials. We excluded projects with large number of zero-commit forks and repositories with huge numbers of forks and commits (top 1%).

A second threat to validity may come from our gender classifier. The accuracy of the classifier is limited by the information users display on GitHub. Many users do not use their real names so we cannot extract their gender information reliably [195]. Some users display names in a language for which our gender classifier does not have data. Moreover, there are many top female developers from East Asia [233]. It is difficult to verify their gender identity because their names are gender neutral and their profile pictures are not necessarily their own photos. Furthermore, our gender classifier, as any automatic classifier we are aware of, is based on the assumption of binary gender, and as such our work cannot explicitly take into account contributions by non-binary software developers.

Third, we used a single coder for the open ended survey questions which might result in a subjective interpretation of the responses. We attempted to mitigate this threat by building on established categories.

Finally, statistical modeling required many operational decisions (*e.g.*, time windows, length of inactivity): ours follow best practices and prior work. Again following best practices, we tested sensitivity of our operational decisions. Given space restrictions, we prioritized replicability and validity, reporting all decisions made, but in cases of insensitive parameters did not always discuss the rationale for a specific value.

3.7 Conclusions

In this paper we have studied the impact of social capital on sustained participation of open source contributors and, in particular, on gender differences in this impact. We have performed a mixed-methods empirical study combining survival analysis on a longitudinal data set of 58,091 open source contributors and their GitHub contributions, with a survey of 98 developers. Our studies show that in general social capital positively affects sustained participation in open source on GitHub. For women, diversity of the project members' expertise becomes crucial to sustain their participation: we found that higher team diversity along dimensions of programming language expertise is associated with decreased risk of disengagement both short and long term.

Our secondary contribution is the very first gender inference tool explicitly targeting Chinese, Japanese, and Korean names, achieving 83.62% accuracy overall, and at least 60.00% on (South) East Asian names. This opens multiple directions of further research from replication of earlier gender studies [62, 212, 58, 7] for East Asian contributors to exploration of new datasets such as Stack Overflow in Japanese.[5]

In the same way as we have studied the impact of language heterogeneity on the disengagement of women, future work should also consider the impact of gender diversity and gender homophily, i.e., preference of people to interact more with people of the same gender, of the teams on the disengagement of women [58, 67]. Furthermore, our study can be replicated to investigate the relation between social capital and sustained participation on other platforms, *e.g.*, Stack Overflow, and the impact of different demographic aspects.Finally, understanding the relation between social capital and sustained participation on GitHub is the key to designing appropriate interventions aiming at ensuring engagement of women in open source software projects more broadly.

[5] https://ja.stackoverflow.com/

Chapter 4

Detecting Interpersonal Conflicts

Interpersonal conflict in code review, such as toxic language or an unnecessary pushback, is associated with negative outcomes such as contributors' disengagement from OSS. Automatic detection is one approach to prevent and mitigate interpersonal conflict. Two recent automatic detection approaches were developed in different settings: a toxicity detector using text analytics for open source issue discussions and a pushback detector using logs-based metrics for corporate code reviews. This chapter tests how the toxicity detector and the pushback detector can be generalized beyond their respective contexts and discussion types, and how the combination of the two can help improve interpersonal conflict detection. The results reveal connections between the two concepts and signals that can reflect potential interpersonal conflict.

4.1 Introduction

In online communities and offline workplaces alike, interpersonal conflicts, understood broadly as including hostility, hate, aggression, toxic language, bullying, etc, has been a major concern and topic of research [240, 241, 242]. The consensus is not only that such forms of interaction are antisocial, but also that they are all associated with negative outcomes in the communities or groups where they take place, including decreased well-being, job satisfaction, stress, and turnover [44, 243, 46]. In addition, these outcomes tend to disproportionately affect members of underrepresented groups [244, 245, 246].

In software engineering, the problem of interpersonal conflicts is also well recognized. For example, in software development, some communities and maintainers have a reputation for being toxic [247, 248, 249]. Although relatively milder, impolite language is seen as a barrier to newcomers [31, 88]. There are repeated anecdotes of sexist behavior, harassment, or contributors concealing their identity to avoid abuse [5, 12, 195, 133, 51]. More broadly, evidence is also starting to emerge about anger [154], negative emotions [250], impoliteness [251, 252], pushback [47], or directly toxicity in issue discussions [253, 46, 254, 255], code reviews [256], and Gitter developer communication [257]. The programming-related Q&A platform Stack Overflow is also notorious for being 'toxic' [258].

However, despite comparable agreement about the importance of the problem, there is relatively less progress in software engineering compared to other domains in terms of automatic detection for prevention or mitigation [259, 260]. Several factors contribute to this lag, including inherent difficulty of the problem, but also domain specificity of some toxic interactions and scarcity of labeled data.

Prior research on automatic detection of toxicity and related constructs in software engineering has room for improvement. In particular, we note that approaches published previously in the software engineering literature have generally all been based on textual analytics [46, 261]. For example, Ramen *et al.* [46] experimented with different sets of features, all text-based, to train a classifier to detect open-source software (OSS) toxic issue discussions, which is defined as "rude, disrespectful, or unreasonable comment[s] that [are] likely to make someone leave a discussion" – a definition of toxicity used also in other public discussion forums such as Wikipedia or the New York Times, originating from Google's project Jigsaw [262]. However, follow-up work by Sarker *et al.* [257] showed that Raman *et al.* 's approach has limited generalizability.

Meanwhile, researchers have long been arguing that meta-infor-mation can be very useful to refine inconclusive classification [263]. For example, people with a history of hate speech are more likely to engage in such behavior again than people without any history [264]. In software engineering, Egelman *et al.* [47] showed that using only meta-information can detect pushback, defined as "the perception of unnecessary interpersonal conflict in code review while a reviewer is blocking a change request."

Notably, the two concepts – 'toxicity' as operationalized by Ramen *et al.* [46] and 'pushback' as operationalized by Egelman *et al.* [47] – are similar, but distinct. For instance, while some types of Egelman *et al.*'s pushback could be considered toxic (*e.g.*, personal attacks), others would not (*e.g.*, persistent nitpicking). Moreover, the types of software discussions analyzed and the study settings in the two studies are arguably very different — Egelman *et al.*'s classifier was applied only on code reviews internally at Google and Raman *et al.*'s classifier was applied only on public GitHub issues (not code reviews). Despite these difference, it seems possible that these two approaches could inform one another as a way to improve detection of interpersonal conflict.

In this paper, we contribute: (1) a comparison of how toxicity and pushback manifest in open source and in a company, and (2) a systematic evaluation of our ability to predict toxicity and pushback in different settings and using different approaches. To this end, we use existing and new labeled datasets that capture both concepts in open-source and corporate code reviews. We use 10-fold cross-validation to evaluate and compare the two previous classifiers and also develop a new combined classifier using features from both. Our results provide insights on how these classifiers work in different contexts. The comparisons and discussion also shed light on the relationship between the two concepts, toxicity and pushback, and the two settings, open source and corporate.

By improving the accuracy of automated approaches to detect toxicity, pushback, and possibly other forms of interpersonal conflict in software discussions, this research paves the way for designing tools to prevent, mitigate, and further study these phenomena, including designing interventions to offer just-in-time guidance to developers in such situations. A detector can also be a powerful tool for researchers studying the effectiveness of tool design and other interventions. More generally, this research offers an opportunity to apply a technique to both open and closed source software, possibly benefiting from synergies, a rarity in software engineering research, in our experience.

4.2 Related Work

This paper builds directly on two recent approaches to detecting interpersonal conflict in software engineering artifacts, by Egelman *et al.* [47] and Raman *et al.* [46]. In Egelman *et al.*'s study at Google, the authors conducted interviews to develop the concept of *pushback* and designed logs-based metrics to detect pushback in code reviews. These metrics were rounds of a review, active reviewing time, and active shepherding time. Their logistic regression model obtained high recall (93%–100%) and low precision (6%–11%).

The other approach that this paper builds directly on is that of Ramen *et al.* [46]. The authors manually annotated toxic issue threads from projects on the GitHub platform, and experimented with outputs from different sets of generic text-based classifiers to train a new classifier to detect toxic issue discussions specific for open source. They reported the highest 10-fold cross-validation accuracy when combining Stanford's Politeness Detector [155] with Google's Perspective API.[1] The present paper expands on Raman *et al.* 's text-based features, compares them with Egelman *et al.*'s classifier [47], and experiments with combining the two classifiers.

In addition to the pretrained general-purpose linguistic tools used by Raman *et al.*, we also explore other linguistic techniques to detect interpersonal conflict. Vocabulary-based approaches have been used for text classification. Open-vocabulary analysis extracts features from the text being analyzed using statistical methods [265]. For example, Sood *et al.* [266] showed that an SVM classifier using binary presence and frequency of n-grams as features can be used to predict personal insults on social news sites. Monroe *et al.* [267] showed that the log odds-ratio of an n-gram (the frequency of being in one group of text divided by 1 minus the frequency) in two different groups can be used to identify n-grams that are over-represented in one group relative to the other. We build on Monroe *et al.*'s work in Section 4.5 by attempting to find out if there is a set of vocabulary that can distinguish between the positive labels (toxic or pushback) and the negative labels (non-toxic or non-pushback).

Closed-vocabulary analysis relies on predefined lists of words as features. Building on the classic linguistic theory of politeness by Brown and Levinson [268], Danescu-Niculescu-Mizil *et al.* [155] developed a computational parser for politeness strategies. Politeness theory divides politeness strategies into *positive politeness* and *negative politeness*. Positive politeness strategies encourage social connection and rapport, such as gratitude, optimistic sentiment, solidarity, etc. Negative politeness strategies try to minimize the imposition on the hearer, for example, by being indirect or apologizing for the imposition [269, 270, 268]. On the other hand, impolite behaviors can be direct questions (*e.g.*, "why?") or sentences that start with second-person pronouns, which may sound forceful. Prior studies showed that the politeness strategy parser [271] is able to predict if a conversation may turn awry [272] and can generalize well to various contexts. We build on this work by using politeness strategy features in our classifiers.

Finally, in the software engineering community, sentiment analysis [273] is a popular technique for analyzing issue discussions [154], pull request comments [274], and forum discussions [275]. Prior work has shown that sentiment analysis classifiers need to be trained using software engineering data because many traditionally negative phrases may have

[1] https://perspectiveapi.com/

neutral sentiment in the context of software engineering [157], for example, "execute" (for a survey see Zhang *et al.* [276]). Popular software engineering sentiment analysis tools include Senti4SD [275] and SentiCR [277]. Senti4SD, developed by Calefato *et al.* [275], is trained on 4,000 posts extracted from Stack Overflow. This dataset is part of the Collab Emotion Mining Toolkit [278]. SentiCR [277] is trained on 1,600 manually labeled code review comments. In our study, we build on this work by using sentiment analysis developed for code reviews as a feature in our classifiers.

More generally, our work can be seen as related to the community smells literature, *i.e.*, sub-optimal developer community structures that may lead to lower productivity [279, 280], as interpersonal conflict partially overlaps with some types of community smells. Some of the most common community smells are Lone Wolf, Organization Silo, and Bottleneck. There are some attempts to detect community smells automatically. Magnoni [281] extended the classifier CodeFace that was built for code smell detection and applied it on open-source contributors' networks. CodeFace4Smells tries to detect community smell by detecting certain types of sub-communities. Building on CodeFace4Smells, Huang *et al.* [280] built a machine learning model that can detect the three most common community smells. Huang *et al.* incorporated sentiment features such as mean anger and mean joy. Their model can also predict if a developer leaves a community after being affected by community smell. Palomba *et al.* [282] performed information gain analysis on several machine learning models and found that lines of code, churns, and period commits are among the features that contribute the most to detecting community smells.

4.3 Research Questions

Our overarching goal is to bridge the gap between the existing literature on toxicity [46] and pushback [47] in software development. Besides the two concepts themselves, there are three fundamental differences between the prior work studies in this area, which we systematically explore in this paper: (1) the context (open- *vs.* closed-source), (2) the type of discussion (issues *vs.* code review), and (3) the approach to classify (text-based *vs.* logs-based). Overall, we answer the following research questions and sub-questions:

First, we explore how well the two classifiers generalize beyond the respective settings in which they have been developed, while maintaining their specific target concepts (toxicity and pushback) and fundamental approaches to classification (text- and logs-based):

RQ$_2$. *How well do existing classifiers generalize across context and type of discussion?*

To answer this question, for each classifier we explore one additional setting beyond the one in which they have been developed. For the toxicity classifier [46], we experiment with open source code reviews in addition to the original issue discussions. Similarly, for the pushback classifier [47], we experiment with comments on open-source pull requests, the approximate equivalent of the original Google code reviews:

RQ$_{1.1}$. *How well does a text-based toxicity classifier designed for open-source issues perform when classifying toxicity in open-source pull requests?*

Table 4.1: The relationship between our four datasets and their corresponding RQs.

	Classifiers			Number of Data Points
	Text-based	Logs-based	Combined	
D1 Toxic Open-Source Issue Comments	Raman *et al.* [46]	RQ2.2	RQ3.1	80 toxic, 160 non-toxic
D2 Toxic Open-Source Code Review Comments	RQ1.1	RQ2.2	RQ3.1	102 toxic, 204 non-toxic
D3 Pushback in Corporate Code Review	RQ2.1	Egelman *et al.* [47]	RQ3.2	493 pushback, 809 non-pushback
D4 Pushback in Open-Source Code Review	RQ2.1	RQ1.2	RQ3.2	201 pushback, 323 non-pushback

RQ$_{1.2}$. *How well does a logs-based pushback classifier designed for corporate code reviews perform when detecting pushback in open-source code reviews?*

Second, given the theoretical overlap between the concepts of pushback and toxicity, we explore how well the two fundamental approaches to classification, text-based (toxicity) and logs-based (pushback) generalize to detecting the other concept if appropriately trained on relevant data for that other concept:

RQ$_3$. *How well do existing classifiers generalize for both toxicity and pushback?*

RQ$_{2.1}$. *How well does a text-based (toxicity) classifier perform when classifying pushback, in both open and closed-source code reviews?*

RQ$_{2.2}$. *How well does a logs-based (pushback) classifier perform when classifying toxicity in open-source code reviews and issue discussions?*

Finally, we explore to what extent using design insights from one classification approach can be used to improve on the other:

RQ$_4$. *To what degree can combining existing approaches improve detection of toxicity and pushback?*

RQ$_{3.1}$. *How well can a combined text- and logs-based classifier classify toxicity?*

RQ$_{3.2}$. *How well can a combined text- and logs-based classifier classify pushback?*

For completeness, in addition to answering these questions, we also replicate the original experiments on toxicity in open source issues [46] and pushback in Google code reviews [47].

4.4 Datasets

To answer our research questions, we used a mix of existing (whenever possible) and new datasets on toxicity and pushback. First, we used the two existing data sets from prior work on issue toxicity in open source [46] and code review pushback at Google [47]. Additionally, we created two new datasets on code review toxicity in open source and code review pushback in open source. Table 4.1 displays each of these four datasets as a row, labeled D1-D4, summarizes how each of our research questions and the prior work relates to each data set, and describes the size of the datasets.

4.4.1 Design Decisions and Tradeoffs

Before describing each dataset in detail, we note several important high-level design decisions, assumptions, and tradeoffs we had to make when creating the two new datasets, and in order to meaningfully compare results across all four datasets.

Unit of labeling In the original toxic issue comments dataset by Raman *et al.* [46], ground truth labels are available for individual comments and the issue thread-level toxicity labels are an aggregation of comment-level labels, *i.e.*, if there is at least one comment labeled as toxic, the entire discussion is labeled as toxic. In contrast, the pushback code review dataset by Egelman *et al.* [47] contains only thread-level labels. Since we are reusing these datasets without relabeling, we maintain the same unit of labeling also in the two newly created datasets of the same concept.

Unit of classification Our experiments focus on classifying toxic or pushback entities at the thread level, because the logs-based metrics, such as the rounds of review, used by Egelman *et al.* are not applicable for individual comments. However, because the text-based classifier works at the comment level, for pushback datasets where we only have thread-level labels, we had to assign each comment the same label as the thread-level label. We will discuss the limitation when we present the results.

The notion of code review Our two new code review toxicity and pushback datasets are extracted from open-source projects on the GitHub platform whereas Egelman *et al.* 's dataset [47] was extracted from internal Google code reviews. In addition to the differences between the corporate and open-source contexts in terms of culture, process, and their observed consequences, the mechanics of code reviewing also differ. Google uses a proprietary dedicated code review management system [283] where all review comments are associated with specific code changes. On GitHub, projects typically manage code reviews as part of pull request threads. However, even though canonically code review comments on GitHub are expected to be attached to specific lines of code and can therefore be distinguished from more general discussion comments part of the same pull request thread, practices vary widely across projects [284]. For reasons of uniformity across projects when sampling candidates for manual labeling, and since we expect that indicators of pushback may occur across pull requests as a whole, not just review comments attached to specific changed lines, we consider the conceptual equivalent of a Google code review to be an entire GitHub pull request thread, including all its general and line-specific comments, *i.e.*, an "open-source code review thread" hereafter.

Representativeness When sampling toxicity and pushback pull request candidates for manual labeling, we use several heuristics to narrow down the search space (details below) instead of random sampling. While this compromises the statistical representativeness of our datasets, it is necessary to do this since the two phenomena we study are relatively rare;

random sampling is unlikely to discover many, if any, instances of these phenomena. We note that this is not only a limitation of the two prior work studies we build on, but also of all similar work on hate speech detection *etc.* [285]. Alternative approaches to building labeled datasets for hate speech detection are, as of 2021, still actively being researched [285].

Open source vs corporate metrics While we try to replicate Egelman *et al.* 's pushback detection method, some measures are unfortunately not observable on GitHub. For example, we cannot replicate "shepherding time," which in Egelman *et al.* 's study is the total amount of time an author spent actively viewing, responding to reviewer comments, or working on the selected code change, including looking up APIs or documentation. The public GitHub trace data about pull request threads captures only wall clock times, which is an overapproximation of the active shepherding time. We are particularly interested in evaluating how well such approximation metrics, that are less precise but more widely available outside of a corporate setting, can capture the same phenomena.

4.4.2 Toxic OSS Issues (D1; pre-existing)

This dataset, originally created by Raman *et al.* [46], consists of 80 GitHub issue discussions labeled as toxic by the authors. Starting from the GHTorrent database [84], Raman *et al.* [46] identified potentially toxic issue comments using the keyword "attitude" (the authors of the toxic comments are often criticized in the same thread by others, typically the project maintainers, about their attitude), and from issue threads "locked as too heated"—one of the mitigation strategies afforded by the GitHub platform. Raman *et al.* then manually reviewed a sample of candidate issue threads from this initial list and assigned ground truth toxicity labels.

We decided to replace the control group in Raman *et al.*'s dataset [46] because we noticed that those non-toxic comments' total number of characters is significantly shorter than for the toxic comments. Since a priori we have no reason to expect that toxic issues are generally longer than non-toxic issues, and we want to capture other aspects of toxic comments, we compiled a new set of non-toxic issues. Inspired by Egelman *et al.* [47], we constructed stratified samples by propensity score matching on the length of all comments within an issue thread (which is not used in any of our prediction models), after excluding code segments and comments from obvious bots [252], *e.g.*, a continuous integration tool. Our new set of non-toxic issues contains two non-toxic issues for every toxic issue.

4.4.3 Toxic OSS Code Review (D2; novel)

We compiled a dataset of 102 toxic open-source code review threads (*i.e.*, pull request threads with all their associated comments) and a separate corresponding control group of non-toxic open-source code review threads, using a similar approach to the one originally taken by Raman *et al.* [46] for issues. Specifically, we use three heuristics to narrow down the search space for candidates in the GHTorrent [84] database, followed by manual review and labeling. Egelman *et al.* [47] showed in their study of pushback that inter-rater agreement is very high when using multiple annotators, implying that a single annotator is sufficient. One author of the paper carried out the labeling independently, assigning "toxic" and "non-toxic" labels to the threads as a whole if at least one of the comments was considered to be toxic; when in doubt, we discussed the respective examples as a group and assigned labels collectively.

The three heuristics were:

- Locked as "too heated"—this built-in GitHub mitigation mechanism is available for both issues and pull requests; or
- Containing the keyword "attitude"; or
- Containing "code of conduct", a novel addition relative to Raman *et al.* 's heuristics [46]. We anecdotally observed that a project's code of conduct, when present, is invoked by maintainers when responding to a toxic comment.

Then, as in dataset D1, we performed propensity score matching on the total length of comments to assemble a control group containing two non-toxic open source code reviews for every toxic one.

4.4.4 Pushback in Corporate Code Review (D3; pre-existing)

We used the collection of code reviews gathered by Egelman *et al.* [47] from Google's internal corporate repository. The authors collected these using two methods:

First, Egelman *et al.* [47] pulled a stratified random sample of code reviews, then surveyed authors, reviewers, and other engineers about whether they perceived each code review as having elements of "pushback." The authors then labeled a code review as containing pushback if at least one respondent noted that the review contained at least one element of pushback. Code reviews are labeled as not containing pushback if (a) at least one person responded to a survey about it, and (b) all survey responses about that code review indicated that no elements of pushback were present.

Second, those same respondents could report a code review that they thought contained pushback. They labeled these reported code reviews as "containing pushback", except that we discarded those that participants indicated were problematic only because of excessive review delays, which are not part of Egelman *et al.* ' definition of pushback [47].

4.4.5 Pushback in OSS Code Review (D4; novel)

To construct an open source counterpart to the corporate code review pushback dataset, we replicated the survey instrument used by Egelman *et al.* [47], with only surface-level modifications to adapt to pull requests and their specifics on the GitHub platform instead of Google-specific terminology.

We then compiled a sample of GitHub code reviews that each:

- had at least 10 comments, to ensure that at least some amount of interpersonal interaction was present, and
- had no more than 50 comments, to limit the reading effort expected from survey respondents.

Additionally, to ensure some diversity in code review outcomes, half of the sampled code reviews were merged pull requests and half were closed without being merged. We emailed survey invitations to the authors and reviewers who display their emails publicly.

As with Egelman *et al.* 's survey [47], we also asked participants to report other code reviews that they thought contained pushback; 63 were reported this way. The reasons that these code reviews were reported as pushback are shown in Figure 4.7 in Appendix. We then labeled these discussions using the survey data in the same way as in Dataset D3. As a result, this dataset contains only conversation-level labels.

Since one can maximize the recall of a classifier by predicting all data points as positive, the minimum precision score is the percentage of positive data points. Therefore, to make D3 and D4 more fairly comparable, we downsampled D4's negative data points to match the positive-negative ration in D3. In the end, D4 contains 201 pushback threads and 323 non-pushback threads.

4.5 Exploratory Analysis

As a first step, before applying machine learning, we explored how well a more basic word-frequency approach could distinguish discussions with one label compared to the other (*e.g.*, toxic *vs.* non-toxic) in each of the four datasets. To this end, we used an open-vocabulary analysis [267] to automatically identify words and phrases that are used distinctly more often in one label than the other, and then manually reviewed these looking for themes. This analysis serves two purposes. First, it helps to triangulate that the manually assigned labels are meaningful, if "obvious" differences between the two classes are detectable using this independent approach. Second, it informs the design of more sophisticated automated classification, by identifying promising features.

Concretely, for the automated part we used log odds-ratio with Dirichlet prior [267] to identify n-grams that are significantly overrepresented in positive labels, *i.e.*, those labeled as toxic or pushback, compared to the negative labels, *i.e.*, those labeled as non-toxic or non-pushback. Since our data sets do not have an equal volume of text, we measured frequency using the log of an n-gram's odds-ratio. Because some n-grams may appear only in one label and not the other, we added a smoothing Dirichlet to the vocabulary. We pre-processed the text by removing URLs and numbers. We did not remove stopwords before performing the analysis because removing them can interrupt sentences and potentially eliminate some meaningful n-grams. We then ranked n-grams by z-scores and kept those with absolute z-scores above 2.326, which corresponds to the statistical significance cutoff of $p < 0.01$. Finally, we kept the 10 unigrams, bigrams, and n-grams with the highest positive z-scores (from positive labels) and 10 with the lowest negative z-scores (from negative labels).

We then manually examined the usage of these n-grams in our data sets by sampling comments containing them. We looked for patterns in these comments that could help us distinguish toxic or pushback comments from non-toxic or non-pushback ones, respectively. That is, we applied this process to all four of our datasets

To illustrate the results of this exploratory analysis, consider the results for dataset D2 Toxic Open-Source Code Review Comments in Table 4.2. In the table, empty cells indicate that no more n-grams were above or below the z-score cutoff. Due to space constraints, the tables (Tables 4.3, 4.4, and 4.5) for the remaining three data sets are shown in Appendix. Below, we describe several patterns that we observed from this analysis.

Second Person Pronouns One clear pattern we can observe from the word frequencies is the use of the second person pronoun "you" in toxic text, including phrases like "you are",

Table 4.2: N-grams that are over-represented in either class in *D2 Toxic OSS Code Review Comments*. N-grams with second-person pronouns are in bold. N-grams with software engineering terms are underlined.

	unigram	z-score	bigram	z-score	ngram	z-score
Toxic	**you**	12.172	it is	5.555	**if you want**	3.397
	people	7.292	**you want**	4.81	it is not	2.712
	even	7.097	that is	4.272	**do you think**	2.576
	do	6.71	going to	4.256	**you need to**	2.397
	what	6.644	**you are**	4.187		
	is	6.373	trying to	4.053		
	want	6.078	**if you**	3.682		
	your	5.796	to do	3.668		
	because	5.657	do not	3.556		
	why	5.547	**you think**	3.539		
Non-toxic	<u>tests</u>	-4.773	**could you**	-2.815		
	<u>unit</u>	-4.858	<u>the pull</u>	-2.889		
	vs	-4.982	as the	-3.137		
	<u>file</u>	-5.15	and the	-3.143		
	<u>files</u>	-5.165	<u>of files</u>	-3.296		
	for	-5.574	we can	-3.48		
	<u>test</u>	-5.76	<u>pull request</u>	-3.668		
	from	-5.872	<u>code to</u>	-3.856		
	at	-6.732	to the	-4.031		
	line	-6.782	instead of	-5.004	<u>the pull request</u>	-2.276

"if you want". "You" is the unigram with the highest z-score in both D1 (Table 4.3) and D2. In Table 4.2, n-grams with second-person pronouns are in bold.

To investigate further, from D1 and D2 we randomly sample 10 toxic comments and 10 non-toxic comments that include "you." Some of these comments involve direct attacks on the second person recipient, such as "[y]ou don't care to be a part of the project," "[y]ou are expected to comply," "[y]ou decided to insult [...]." This echoes what Danescu-Niculescu-Mizil *et al.* [155] found: the use of second-person pronouns at the beginning of a sentence is more likely to be impolite. The same pattern is observed In D3 (Table 4.4).

In non-toxic comments in D2, the only n-gram that contains "you" is "could you", which is a negative politeness strategy that tries to minimize the imposition on the hearer by being indirect. The counterfactual form "could" is more polite than the future-oriented variant "can" [155]. This is also true in D3, where we again see some hedge words and other politeness strategies, such as "could you", "should be", and "seems" among non-pushback code reviews.

Gratitude Gratitude is another common theme in non-pushback text, both in open and closed source code reviews (D3 and D4 (Table 4.5)). These n-grams included "thanks" and "thanks for" that appear among non-pushback code review comments.

Technical Discussion In D1 and D2, we see many software engi-neering-related n-grams, *e.g.*, "tests" and "the pull", among non-toxic comments but almost none among toxic comments.

In D3 and D4, we likewise see more technical terms among non-pushback comments. In Table 4.2, n-grams with software engineering terms are underlined.

Code of Conduct We occasionally see “code of” and “the code of” appear in the top-10 lists. Typically, these two n-grams appear when referring to “the code of conduct”, often as a reminder that someone violated the code of conduct. For example, one contributor wants the maintainer “to enforce the code of conduct [...].” Interestingly, we observe this pattern in D4 (pushback in open source code reviews), which was sampled without using this as a search term.

No Pattern and Overfitting Finally, among all four datasets, we see some n-grams with no discernible rationale for why they might be indicators or contraindicators of toxicity or pushback. For instance, in Table 4.2, the bigrams consisting of only stop words, *e.g.*, “as the”, “and the”, and “to the”, appear to just be noise, rather than true indicators of non-toxic open-source code review. As an example of overfitting, the top unigram in D3 (“<tech1>”) indicates a widely-used, Google-specific piece of technology.

Overall, this exploration confirms that discussions in the positive labels, tend to shift focus away from the technical aspects themselves and onto interpersonal issues. The ground truth labels on all four datasets appear meaningful, since there are noticeable differences in the relative frequency of words and phrases between discussions with presence and absence of toxicity and pushback. Moreover, the analysis implies that there is substantial overlap between the two concepts of pushback and toxicity, suggesting that incorporating text-based features into classifiers for both concepts is worthwhile. However, the absence of a clear pattern for many n-grams suggests that a purely frequency-based approach would be insufficiently discriminatory for an accurate classifier. In what follows, we introduce more sophisticated classification approaches.

4.6 Methods for Classification

4.6.1 Building classifiers for toxic comments and pushback in code reviews

Text-based features In this paper, we reuse and improve the classifier developed by Raman *et al.* [46], which takes outputs from several text-based pretrained classifiers as features. We first preprocessed the text by removing URLs, quotes, numbers, *etc.* Then we feed the text into the following three pre-trained NLP classifiers, and use the outputs as features.

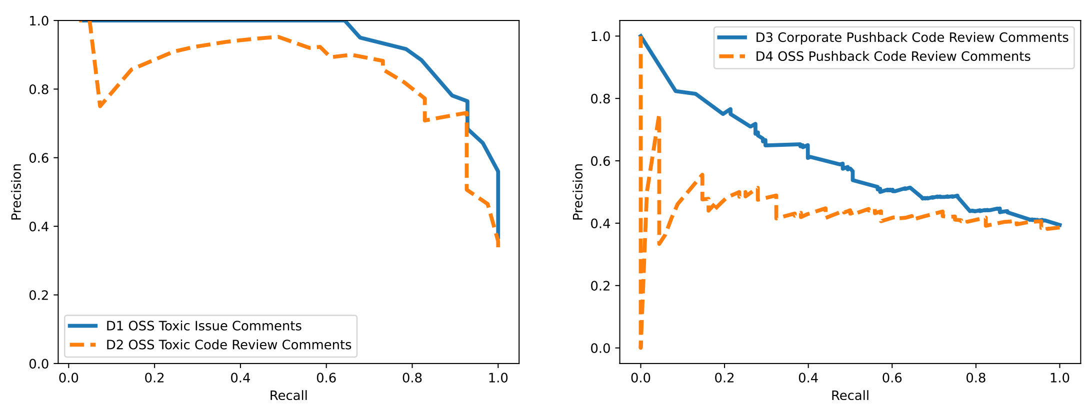
Following Raman *et al.* [46], we collect (1) the toxicity score and identity attack score from the Perspective API ([0, 1] range, with 1 being the most toxic/aggressive) and (2) count the occurrences of different politeness strategies using the politeness parser [155, 271] (normalized to [0, 1]). In addition, we used (3) a sentiment analysis tool developed for software engineering code review comments, SentiCR [277], with reportedly better performance on GitHub data than other sentiment analysis tools [276]. The output from SentiCR is either positive sentiment (1) or negative sentiment (-1).

Logs-based features Because we are interested in answering whether the pushback classifier by Egelman *et al.* [47], which uses logs-based features, can be applied to open-source code review comments (RQ1), we calculated logs-based metrics for D2 and D4, the two novel datasets. Egelman *et al.*'s work on code review in the company used rounds of review, active reviewing time, and active shepherding time to build a classifier for pushback. They defined:

- *Rounds of review* as the number of batches of contiguously authored comments, as it "captures the extent to which there was back-and-forth between the author and reviewer."
- *Active reviewing time* is "the time invested by the reviewer in providing feedback," which includes actively viewing, commenting, or working on code review.
- *Active shepherding time* is the time "the author spent actively viewing, responding to reviewer comments, or working on the selected CR, between requesting the code review and merging the change into the code base."

The above "active" times may include time outside of code review, *e.g.*, editing files, but does not account for in-person conversations.

As discussed in Section 4.4, for GitHub data we could not exactly replicate all three logs-based metrics used by Google, because of differences between Google's code review tool and the GitHub pull request workflow. Therefore, by necessity we operationalized these metrics for open-source code review comments (D2 and D4) differently:



(a) Text-based classifier P-R curves on D1 and D2.

(b) Logs-based classifier P-R curves on D3 and D4.

Figure 4.1: Text-based classifier P-R curves

- We approximated *Rounds of review* as the number of comments on a pull request, since GitHub code review comments are not always grouped into batches the way Google's are.
- We approximated *Active shepherding time* as the time difference between the initial PR post and the last comment. Note that the difference between our shepherding time and the one by the company is that the company uses the actual amount of time an author spent on a code change, whereas ours is the wall-clock time of the entire review process, which may result in longer shepherding time overall.
- We did not attempt to approximate *Active reviewing time*, because we could not distinguish how much of the time between the submission of code and the last comment was taken by reviewers or by the author.

Training We trained a random forest [286] classifier for each classification task because of its accuracy and robustness against overfitting [287, 288].

Following Raman *et al.* [46], we performed 10-fold nested cross validation to find the best model and reduce bias from random data splits. We first randomly split our labeled data into a training set (67%) and a test set (33%). We used stratified sampling to preserve the ratio between labels and ensure that each set contains both positive and negative labels.

We then fit and cross validate a random forest model using the training set for 10 trials. In each trial, the training set is further split into 10 folds randomly. Each fold is used once as a cross validation set, while the remaining 9 folds are used for training. The random forest model learns the best combination of hyperparameters, such as `n_estimators` and `max_depth`, optimizing for F1 score, the harmonic mean of precision and recall.

After each trial, we tested the random forest model with the combination of hyperparameters that produced the highest F1 score during training (67% of the entire labeled dataset) on the held-out test data (33% of the entire labeled dataset).

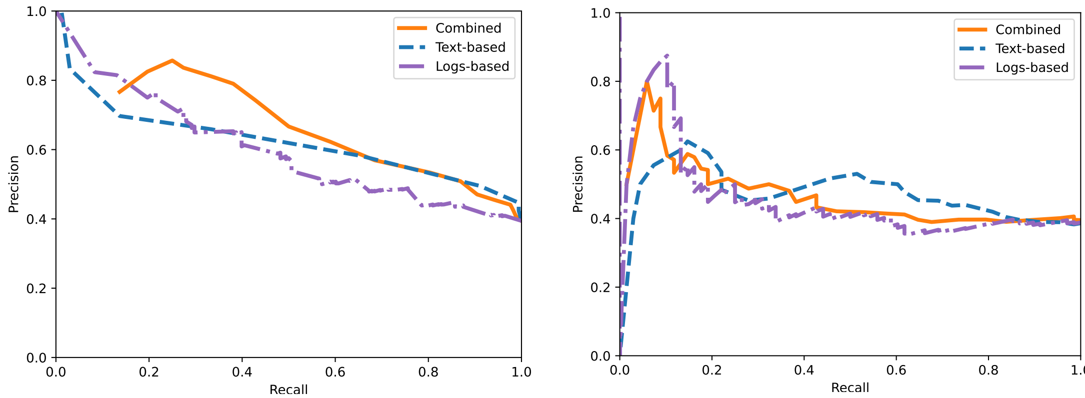
For the text-based classifier, the classification is performed at comment level. Then we aggregate the classifications to form thread-based labels. For pushback datasets (D3 and D4) where we only have thread-level labels, we assign all comments the same label as the thread-level label. For the logs-based classifier, the classification is performed at thread-level.

4.6.2 Classifier Performance Analysis

To evaluate the performance of our classifiers, we computed and compared the Areas Under the Precision-Recall (P-R) Curves, *i.e.*, the P-R AUC scores. Precision tells us how many comments labeled by our classifier as toxic/pushback are in fact toxic/pushback, and recall tells how many toxic/pushback comments in our test dataset are classified as toxic/pushback. P-R curves explore the classic precision/recall tradeoff in applications where the data is imbalanced [289], as is ours — toxicity and pushback are both relatively rare. P-R curves are also commonly used to evaluate classifiers when researchers care more about positive (toxic or pushback) than negative labels. This is also the case in our work — for downstream prevention, mitigation, and future research on toxicity and pushback, we believe that it is more important to identify true instances of toxicity and pushback than it is to identify that some comment or conversation is not toxic or pushback. A P-R AUC score summarizes the performance of a classifier into one value and can be interpreted as the average of precision scores calculated for different recall thresholds, with higher values (closer to 1) being preferable.

To compute the P-R curves, we uniformly vary the classifier's probability threshold for predicting the positive class, which corresponds to exploring the precision-recall tradeoff. To compare classifiers, we performed pairwise t-tests on their P-R AUC scores computed after the 10 cross-validation trials. At each trial, we applied the random forest classifier with the best hyperparameter combination on the held-out test data and computed an AUC score. As a result, from our 10-fold nested cross validation training process, we obtained 10 AUC scores (one per trial). For each t-test, we also report Cliff's delta measure of effect size.

In addition, we estimate the importance of each feature [288] in our random forest classifiers during the training phase, using a standard approach based on the mean overall improvement in a tree's impurity. The impurity, in classification tasks, is measured by the



(a) P-R curves of all three classifiers on D3

(b) P-R curves of all three classifiers on D4

Figure 4.2: P-R curves on pushback classification

Gini index, interpreted as the probability of an item being incorrectly classified if it was randomly labeled according to the distribution of a specific feature [287].[2]

4.7 Results

RQ 2: How well do existing classifiers generalize across context and type of discussion?

To answer this question, we plot the P-R curves by the classifiers using the same features on different datasets and compare the average AUC scores. Figure 4.1 shows one of the curves from the 10 trials.

We start by comparing the P-R AUC scores for the text-based toxicity classifier on D2 (open-source code reviews) relative to the benchmark D1 (open-source toxic issues), answering $\mathbf{RQ}_{1.1}$. The P-R curves are shown in Figure 4.1a. We find that at the thread level, the text-based classifier performs better on D1 than on D2 ($t = 5.640$, p-value $= 0.0001$; Cliff's $\delta = 1$ / large effect; the AUCs are 0.907 and 0.844 respectively).

We manually checked some randomly sampled toxic comments from D1 and D2 that our text-based classifier failed to identify. We found that some of them are responding to toxic behavior. For example, phrases like "you spent a long time insulting people" are responses to someone else's insult and are clearly a signal of the presence of toxicity. Some other ones contain *covert toxicity*, such as sarcasm, entitlement, or the use of "?!" or emojis. Covert toxicity is difficult for language models to detect in general [290]. These comments also have a low predicted toxicity score by our classifier; some even use the word "please" as in "Please consider that this thread [...] is so problematic. [...] get this PR closed ASAP."

The impurity-based feature importance analysis (Figure 4.4a in Appendix) provides some explanations on what features are important in both datasets. The x-axis is the importance score of the features. The sum of importance scores of all features is 1. The two most important

[2]Our code is available at https://doi.org/10.5281/zenodo.6051070

features during the training phase are from the Perspective API. They are followed by three politeness features: second person pronouns, the presence of negative words, (*e.g.*, "begging for complete code review" and "many bugs documented and unresolved"), and the use of first person pronouns. The use of second person pronouns echoes our findings of the word frequency analysis, where we see the use of "you" overrepresented in toxic text.

Reflecting on differences between the issue conversations and code review conversations that could cause the performance degradation when detecting toxicity in the latter case, we speculate two reasons based on exploring the two labeled datasets. One is that many code-specific comments are much shorter than discussion comments, yielding less linguistic information. The other possibility is that the code review conversations in our dataset more often include code chunks and removing inline codes may reduce information for the text-based classifier.

Next we compare the P-R AUC scores for the logs-based classifier on D3 (pushback in corporate code review) and D4 (pushback in open-source code review), answering $\mathbf{RQ}_{1.2}$. The P-R curves are shown in Figure 4.1b. Our results show that the logs-based classifier has a lower performance when transferred to the open-source context, despite being retrained ($t = 40.008$, p-value $< 2.2e-16$; Cliff's $\delta = 1$; the average AUC scores are 0.693 and 0.445 for D3 and D4).

We speculate that there are two main reasons for the lower performance. First, limited by the information publicly available on GitHub, we could only compute measures for two of the three logs-based features used originally inside Google. Therefore, we have less information. Indeed, in D3, reviewing time, the feature missing in D4, ranks as the most important (Figure 4.5 in Appendix). Second, our measure of shepherding time computed for open-source code reviews is only an approximation, using wall-clock time rather than the amount of time spent actively working on code in review. Therefore, the logs-based features we computed for open-source data are not as accurate as those on corporate data.

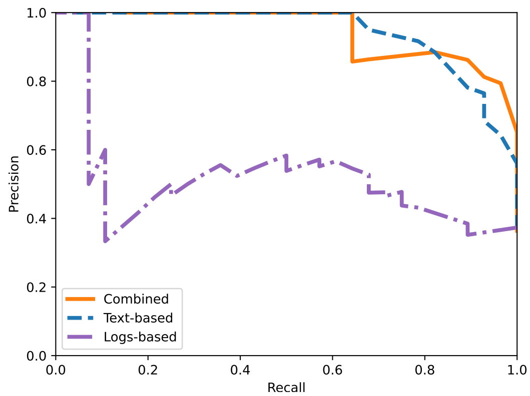
Summary: *Both the text-based classifier and the logs-based classifier have performance degradation when generalizing to other contexts.*

$\mathbf{RQ}_2$: ***How well do existing classifiers generalize for both toxicity and push-back?***

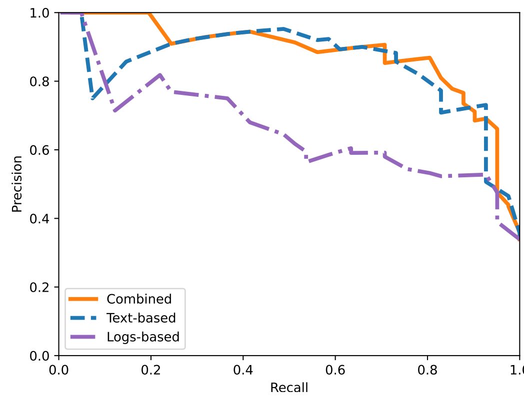
To answer this research question, we compare the performance of the classification approach originally designed for one construct (toxicity or pushback) to the classification approach originally designed for the other construct.

We start by evaluating the performance of the text-based classifier on datasets D3 and D4, compared to the performance of the logs-based classifier as a benchmark, answering $\mathbf{RQ}_{2.1}$. Figure 4.2 shows one of the P-R curves from the 10 trails.

On *D3 Pushback in Corporate Code Review*, the text-based classifier outperforms the logs-based classifier on average ($t = 9.766$, p-value $= 1.304e-08$; Cliff's $\delta = 1$ / large effect; the mean AUC scores are 0.757 and 0.693 for the text-based and logs-based classifiers respectively); note, this logs-based classifier is the one using all three measures of pushback, available inside the company Google. This suggests that pushback as a construct shares many linguistic similarities with toxicity. In addition, the better performance of the text-based classifier suggests that, in a corporate setting, interpersonal conflicts can be more subtle than delay of reviews or excessive comments.



(a) P-R curves of all three classifiers on D1



(b) P-R curves of all three classifiers on D2

Figure 4.3: P-R curves on toxicity classification

For *D4 Pushback in Open-Source Code Review*, comparing the P-R AUC scores shows that, unlike previously on D3, the text-based classifier and the logs-based have a similar performance (t = 0.246, p-value = 0.810; the average P-R AUC scores are 0.447 for the text-based classifier and 0.445 for the logs-based one); note, the logs-based classifier in this case contains only the measures available publicly on the GitHub platform.

One possible explanation is that in contrast to the previous corporate dataset, there are relatively fewer examples of open-source pushback code reviews in our sample that could be traced back to reasons with linguistic markers. Therefore, there is less for the text-based classifier to discern. To test this hypothesis, we compiled a subset of D4, D4-1, containing as positive examples all the reported pushback open-source code review threads that are linked to linguistic markers (Figure 4.7 in Appendix), such as "harsh comments" (39 out of 63 self-reported pull requests), and as negative examples the remaining self-reported pushback open-source code review threads with only likely non-linguistic markers, such as "excessive review delays." Comparing the performance of the logs-based and text-based classifiers on D4-1 does not support our hypothesis: the text-based classifier underperforms the logs-based one ($t = -5.072$, p-value = 0.0002; Cliff's $\delta = -0.86$ / large effect; the average AUCs are 0.566 and 0.679 respectively). The reason could be that pushback threads labeled with linguistic-related reasons are often labeled with non-linguistic ones too, *e.g.*, "requesting a change without justification."

Another possible explanation is that since pushback classification is done at the thread level, within a thread the actual comments indicative of pushback are too rare for the whole text of the threads to be significantly different on average between the pushback and non-pushback classes. To test this, we created dataset D4-2, in which we assigned pushback labels at the comment level. Specifically, we used the responses to our survey asking participants to copy-paste the text fragments indicating pushback, in addition to offering pushback pull requests as a whole, to identify which comments in the thread contained those exact fragments. We then labeled those comments as pushback and all other comments in the same threads as non-pushback. Then we performed the classification and thread-level aggregation as usual.

Comparing the performance of thread-level text- vs logs-based classification on D4-2, we observe that the text-based classifier now outperforms the logs-based one ($t = 2.591$, p-value $= 0.026$; Cliff's $\delta = 0.54$ / large effect; the average AUCs are 0.534 and 0.471 respectively), supporting our hypothesis.

The feature importance analysis (Figure 4.4b in Appendix) for the text-based classifier on both pushback datasets D3 and D4 present some insights into what linguistic features are associated with pushback comments. On both datasets, the toxicity score and identity attack score from the Perspective API have the highest importance. They are followed by several politeness strategies. The third most important feature in D3 is the presence of positive lexicons whereas in D3 is the number of hedge words, such as "likely", "maybe", "seems". Having second person pronouns is also an important feature to classifying D3 Pushback in Corporate Code Review but less so to D4 Pushback in Open-Source Code Review.

Summary: *When detecting pushback, the text-based classifier performs better than the logs-based classifier for corporate code review comments, but they have similar performance for open-source code review comments.*

Next we compare the performance of the logs-based classifier against the performance of the text-based classifier on detecting toxicity, answering $\mathbf{RQ}_{2.2}$. We plotted the P-R curves for the text-based and the logs-based classifiers on D1 and D2, shown in Figure 4.3. We find that the text-based classifier performs better than the logs-based one on both D1 ($t = 45.515$, p-value $< 2.2e - 16$; Cliff's $\delta = 1$; P-R AUC scores are 0.907 and 0.516 respectively) and D2 ($t = 13.591$, p-value $= 2.22e - 10$; Cliff's $\delta = 1$; P-R AUC scores are 0.844 and 0.665, respectively). The good performance of the text-based classifier implies that toxicity is more of a linguistic phenomenon. Meta-data, such as the logs-based features we computed, could not capture enough information to distinguish toxic language.

Summary: *The logs-based classifier does not perform as well as the text-based one when detecting toxic open-source issues and code review comments.*

$\mathbf{RQ}_3$: ***To what degree can combining existing approaches improve detection of toxicity and pushback?***

We start by comparing P-R AUC scores of the text-based and the logs-based classifiers against that of the combined classifier when detecting toxicity, on both D1 and D2, which answers $\mathbf{RQ}_{3.1}$. The P-R curves are shown in Figure 4.3. Overall, we find that the combined classifier has better performance than the logs-based classifiers but is similar to the text-based classifier. On D1, the combined classifier outperforms the logs-based one (a t-test between the logs-based classifier and the combined classifier: $t = -51.975$, p-value $< 2.2e - 16$; Cliff's $\delta = -1$; the AUC scores are 0.516 and 0.895 respectively) but is indistinguishable from the text-based classifier (a t-test between the text-based classifier and the combined classifier: $t = 0.376$, p-value $= 0.712$, the text-based classifier's AUC is 0.907).

Similarly, on D2, the combined classifier outperforms the logs-based classifier (a t-test between the logs-based classifier and the combined classifier: $t = -24.226$, p-value $= 9.001e - 12$; Cliff's $\delta : -1$; AUCs are 0.665 and 0.871 respectively). However, the combined classifier outperforms the text-based classifier (a t-test between the text-based classifier and the combined classifier: $t = -2.3884$, p-value $= 0.0363$; Cliff's $\delta : -0.58$ / large effect; the AUC of the text-based classifier is 0.844).

The feature importance analysis (Figure 4.6a in Appendix) shows that text-based features are more important in detecting toxicity than logs-based features. This suggests that, again, toxicity is more about the language than the logs-based metrics. The toxicity score and identity attack by the Perspective API have the highest importance. They are followed by the two logs-based features, which are followed by several politeness strategies. The use of second-person pronouns is also among the top 5 most important features, which echoes our findings in the word frequency analysis.

Summary: *For toxicity, the combined classifier has a similar performance to the text-based one on toxic issue comments but a better performance on toxic code review comments. The combined classifier performs better than the logs-based one in detecting toxicity.*

Finally, we compare the AUC scores between the text-based and the combined classifier and between the logs-based and the combined classifier when detecting pushback (D3 and D4), which answers $\mathbf{RQ}_{3.2}$. The P-R curves are shown in Figure 4.2.

On *D3 Corporate Pushback Code Review Comments*, the combined classifier performs better than the logs-based (a t-test between the logs-based and the combined classifier: $t = -12.511$, p-value $= 2.108e - 08$; Cliff's $\delta = -1$ / large effect; AUC are 0.693 and 0.755) but about the same as the text-based one (a t-test between the text-based and the combined classifier: $t = 0.363$, p-value $= 0.723$; the text-based classifier's AUC is 0.757).

On the contrary, on *D4 Open-Source Pushback Code Review Comments*, the performance of the logs-based classifier is similar to the the combined classifier ($t = -2.1171$, p-value $= 0.052$; the average AUC scores are 0.445 and 0.455 respectively). Similarly, the combined classifier's performance is indistinguishable from that of the text-based classifier (a t-test between the text-based and the combined classifier: $t = -0.929$, p-value $= 0.373$, the text-based classifier's AUC is 0.447).

From the feature importance analysis on the combined classifier on our two pushback datasets D3 and D4 (Figure 4.6b in Appendix) shows that the logs-based features have higher importance than the text-based ones. Among the text-based ones, toxicity score and identity attack have the highest importance, followed by several politeness strategies.

Summary: *For classifying pushback in code reviews, the combined classifier performs better than the logs-based classifier but about equivalently to the text-based classifier in a corporate setting; and performs about equivalently to the text-based classifier and the logs-based classifier in an open-source setting.*

4.8 Discussion

Classifiers' cross-domain application For $\mathbf{RQ}_1$, we found that prior classifiers' performance [46, 47] degrades when applied to new datasets. For open-source code review comments, one reason may be that, compared to issues, discussions in PRs are generally more technical, and hence, less personal. One reason the logs-based classifier performed relatively poorly in open-source code review may be that we were not able to accurately reproduce one of the corporate pushback features, active shepherding time.

Relationship between toxicity and pushback By answering $\mathbf{RQ}_2$, how well can the classifiers generalize across domains and datasets, we can conclude some relationship exists between the two concepts. Pushback is initially centered around delays in code review, which is associated with lower productivity [47], whereas toxicity is centered more around the negative interactions among contributors during code review [46]. However, Egelman *et al.* [47] reported that, in addition to lengthy reviews, pushback is also characterized by interpersonal conflict. This is supported by our finding that the text-based classifier has a better performance than the logs-based one on pushback detection in a corporate setting, suggesting that pushback in a corporate setting is more subtle than lengthy discussions or delayed reviews. Similarly, in open-source, toxic language is also a significant part of pushback. Among the pushback code review comments users reported, more than half of them have reasons related to communication (Figure 4.7 in Appendix). However, we found that the logs-based features did not improve toxicity detection. This suggests that toxicity is mostly about language, and meta-data cannot capture the nuance.

Corporate vs. open-source settings When answering $\mathbf{RQ}_2$, we were also able to compare the two contexts, corporate and open source. We found that the text-based classifier works better than the logs-based one when classifying corporate pushback. However, it was surprising that the logs-based classifier and the text-based one have similar performance when classifying open-source pushback. This differs from the impression we had from the survey responses. From the survey responses, we observed many complaints about maintainers delaying the review process. When looking at some of the PRs, we saw that many of the maintainers mentioned having a holiday or being busy with day jobs as reasons for the delay. One comment from the open-source pushback survey reflected that "It's not PR and not about code review, but it's about open source world."

Moreover, both the text-based and the logs-based classifiers have better performance on corporate pushback code review comments than on open-source ones. This suggests some differences between the two datasets. Perhaps these differences arise from uniformity in Google's code review practices [283] compared to the multitude of practices used on GitHub [284].

This also raises the issue of transferring our results to other settings. When answering $\mathbf{RQ}_1$, we found that using the same set of features on data from a different context resulted in lower performance. However, the multiple levels of comparisons we conducted in this study can act as a guideline while developing a system for toxicity and pushback detection in other contexts.

Prediction vs. classification In this paper, we performed classification on conversations after they had concluded, largely because logs-based features are not applicable to individual comments. As a result, our current models cannot yet be applied to all scenarios where automated detection of toxicity or pushback are of interest, *e.g.*, comment-level classification for just-in-time intervention. Instead, we target primarily scenarios where thread-level classification is needed, *e.g.*, to reflect on when discussions have gone awry (of interest to practitioners) or to detect and study when, how, and why toxicity and pushback occur (of interest to researchers).

Future work can explore how to use text-based features to do real-time detection and offer editing suggestions. Cherjyan *et al.* [261] proposed a Conflict Reduction System that can rephrase offensive sentences. However, their datasets are heavily focused on swearing and profanity. Our findings can greatly enrich the set of text features that can be used to detect and prevent potential toxic comments.

Text analytics improvements Our text classifier combined three different NLP techniques, but other NLP techniques on larger datasets is a future research direction. Some paths that can be explored include using text embedding [291] or conversational structure [272]. One could also use Snorkel [292], a weak supervision model, to help augment our labeled dataset.

Prior studies have shown that general NLP models may not be directly applicable to software engineering corpora [293, 157]. For example, "error" and "test" are mostly neutral in the software engineering context but have negative connotations in general English. Han *et al.* [294] report that Perspective API can misclassify toxic inputs due to a domain mismatch or novel lexicon of toxicity. Therefore, some fine-tuning is needed on top of the Perspective API to attain better performance. Raman *et al.* [46] suggested fine-tuning a classifier using a domain-specific lexicon. However, this is a difficult task that needs careful design and evaluation. Thresholds and datasets are all variables that can be explored. Moreover, when evaluating the effectiveness of the domain-specific lexicon tuning, how do we decide what words should be in the list and what should not? These questions are worth exploring in the future.

4.9 Threats to validity

Internal validity The data we used for training and testing our classifiers is small in two respects. The first is from a machine learning perspective, where more data often yields more reliable conclusions. The second is from an ecosystem perspective; the data we studied represents a small subset of all the discussions going on within GitHub and Google, likely limiting the generalizablity of our results.

Another limitation is that our data, both existing and newly collected, rely on human raters to judge interpersonal conflict. While Egelman and colleagues' showed some degree of reliability across different raters, nonetheless perceptions of interpersonal conflict invariably differ from person to person. Such differences threaten the true accuracy of our ground truth data.

External validity A major threat to generalizability is the context in which we collected our data. For corporate code reviews, we used data from Google; classifying code reviews in other companies would likely yield different results. Likewise, our other datasets are from GitHub; data obtained from other platforms may also yield different results.

Construct validity The lack of comment-level labels in pushback datasets D3 and D4 likely confused the classifiers using text-based features. Because all comments within a pushback conversation share the same label, some neutral or positive comments are also labeled as pushback. Since our text-based classifier works on the comment level, it can get confused when seeing comments associated with polite strategies (*e.g.*, indirect start) and impolite strategies (direct questions) that are both labeled as pushback.

In our analysis, we bridged concepts and contexts in prior work [46, 47], between open and closed source; and issues and code reviews. However, we did not exhaustively explore this space. For instance, we did not collect data for toxic corporate code reviews or issues. Given the results that the text-based classifier works well on Google's pull requests, using it to detect or understand toxic comments may be worthwhile future work.

4.10 Conclusion

In this paper, we cross-pollinated with two techniques designed to detect interpersonal conflict. In applying these text- and logs-based techniques to broader contexts than those for which they were originally designed, we uncovered several novel insights. For instance, we found that prior work that detected code review pushback using logs data [47] can be improved substantially by analyzing the text contained in those code reviews. While the opposite was not true – logs data did not improve issue toxicity detection – we nonetheless found that logs can be a useful feature in toxicity classifiers. Building on these techniques, we envision a future where tools can help software developers learn from or avoid interpersonal conflict, enabling projects to be more inclusive of a wider variety of contributors.

4.11 Appendix

Table 4.3: Over and underrepresented words in *D1 Toxicity in Open-Source Issues Comments*. N-grams with second-person pronouns are in bold. N-grams with software engineering terms are underlined.

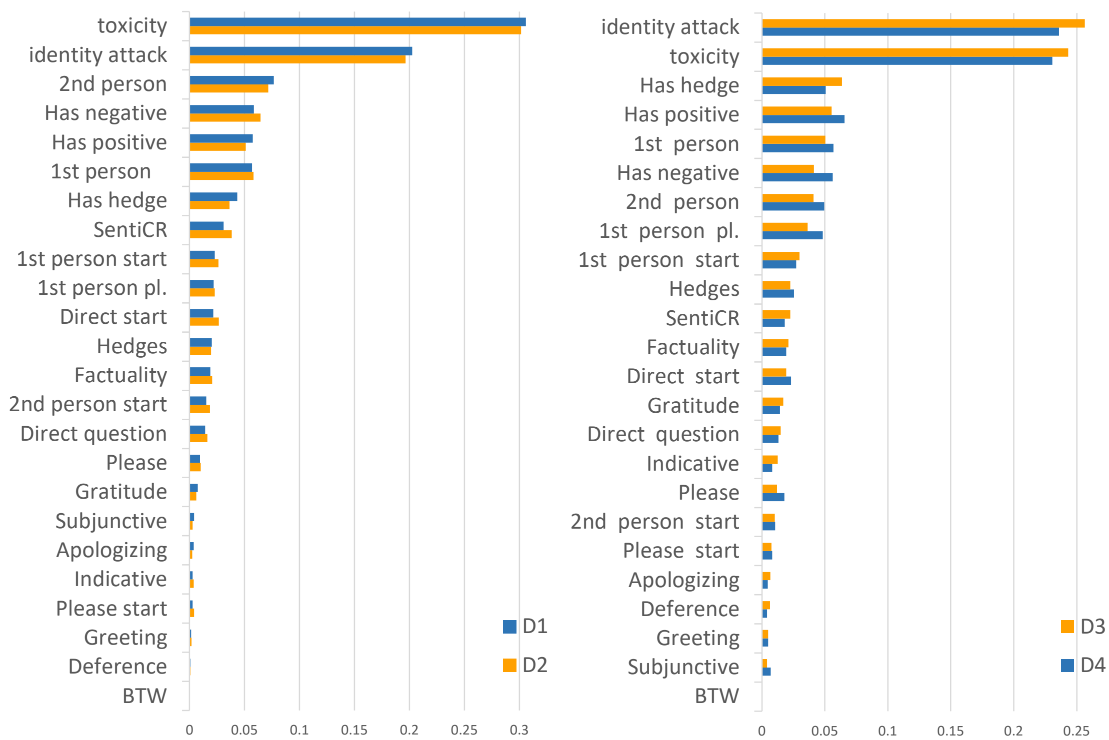
	unigram	z-score	bigram	z-score	ngram	z-score
Toxic	**you**	30.77	this is	12.756	this is not	6.013
	it	23.724	in the	11.822	**you want to**	5.217
	that	22.437	**you are**	11.651	**you need to**	4.869
	of	22.051	it is	10.608	there is no	4.303
	and	21.318	**you have**	9.389	**if you want**	4.272
	is	18.917	to be	9.371	**you have to**	4.036
	this	18.524	**that you**	9.145	to do with	4.036
	your	18.121	**if you**	8.727	**if you want to**	3.971
	have	16.647	to do	7.535	part of the	3.94
	what	15.62	have to	7.514	the problem is	3.799
Non-toxic	via	-3.526	<u>team and</u>	-2.825		
	unit	-3.82	plenty of	-2.838		
	team	-3.871	of experience	-2.954		
	assigned	-3.979	with our	-2.972		
	returns	-4.32	and provide	-2.972		
	<u>function</u>	-4.452	to remove	-3.037		
	item	-5.104	with an	-3.042		
	<u>ticket</u>	-5.121	<u>issue was</u>	-3.263		
	<u>duplicate</u>	-5.528	assigned to	-3.44		
	<u>click</u>	-5.62	looking for	-3.573		

Table 4.4: Over and underrepresented words in *D3 Pushback in Corporate Code Review*. N-grams with second-person pronouns and gratitude are in bold. N-grams with software engineering terms are underlined.

label	unigram	z-score	bigram	z-score	ngram	z-score
Pushback	<tech1>	5.352	**you want**	3.04	**you want to**	2.792
	tests	4.452	want to	2.849	on nov at pm	2.637
	<tech2>	3.683	of these	2.849	nov at pm	2.577
	our	3.599	of our	2.626		
	build	3.564	is to	2.575		
	libraries	3.362	if we	2.525		
	break	3.245	depend on	2.464		
	thing	3.197	we use	2.464		
	see	3.177	the cl	2.441		
	rollback	3.152	this case	2.311		
Non-pushback	submit	-5.338	to represent	-3.831	make sure the	-2.566
	groups	-5.485	to me	-3.834	to do the	-2.64
	feature	-5.514	how about	-3.882	not sure if	-2.69
	<tech3>	-5.64	to submit	-3.96	seems to be	-2.805
	map	-5.664	this function	-4.106	in this cl	-2.813
	rate	-6.042	the new	-4.286	which is not	-2.919
	thanks	-6.303	**could you**	-4.363	**do you have**	-3.189
	section	-6.336	for the	-4.432	how do we	-3.604
	the	-6.492	change the	-4.439	to change the	-4.009
	for	-6.9	**thanks for**	-5.291	**thanks for the**	-4.891

Table 4.5: Over and underrepresented words in *D4 Pushback in Open-Source Code Review*. N-grams with second-person pronouns, gratitude, and "code of conduct" are in bold. N-grams with software engineering terms are underlined.

label	unigram	z-score	bigram	z-score	ngram	z-score
Pushback	runtime	17.511	is of	6.622	**the code of**	3.957
	suggestion	9.676	the project	6.452	the new format	3.721
	argument	9.32	**code of**	6.171	for the new	3.457
	us	8.762	of type	6.006	the commit message	3.185
	people	8.35	the linter	4.638	to the project	3.096
	timer	8.218	read the	4.583	as long as	3.003
	non	7.254	it is	4.313	the number of	3.003
	high	7.068	social media	4.186	to read the	2.957
	requirements	6.29	the old	4.13	just wanted to	2.874
	de	6.276	commit message	4.026	we dont want	2.874
Non-pushback	access	-5.923	the following	-3.402		
	struct	-5.992	an error	-3.412		
	config	-6.197	it seems	-3.536	is going to	-2.311
	tests	-6.282	the same	-3.715	it would be	-2.5
	server	-6.351	**thank you**	-3.786	all of the	-2.5
	line	-6.431	the server	-4.021	this should be	-2.802
	field	-6.632	did not	-4.047	it seems that	-2.872
	build	-7.262	the tests	-4.12	**thank you for**	-2.972
	info	-7.309	file line	-4.287	let me know	-3.111
	error	-7.319	line in	-5.301	file line in	-4.287



(a) D1 vs D2 (b) D3 vs D4

Figure 4.4: Text-based classifier feature importance scores.

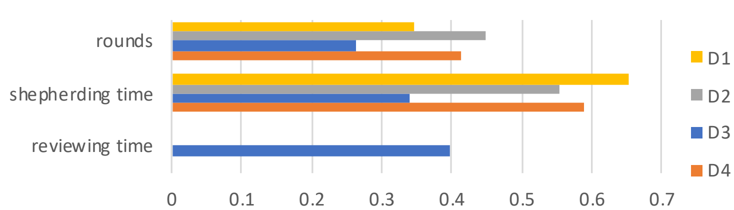
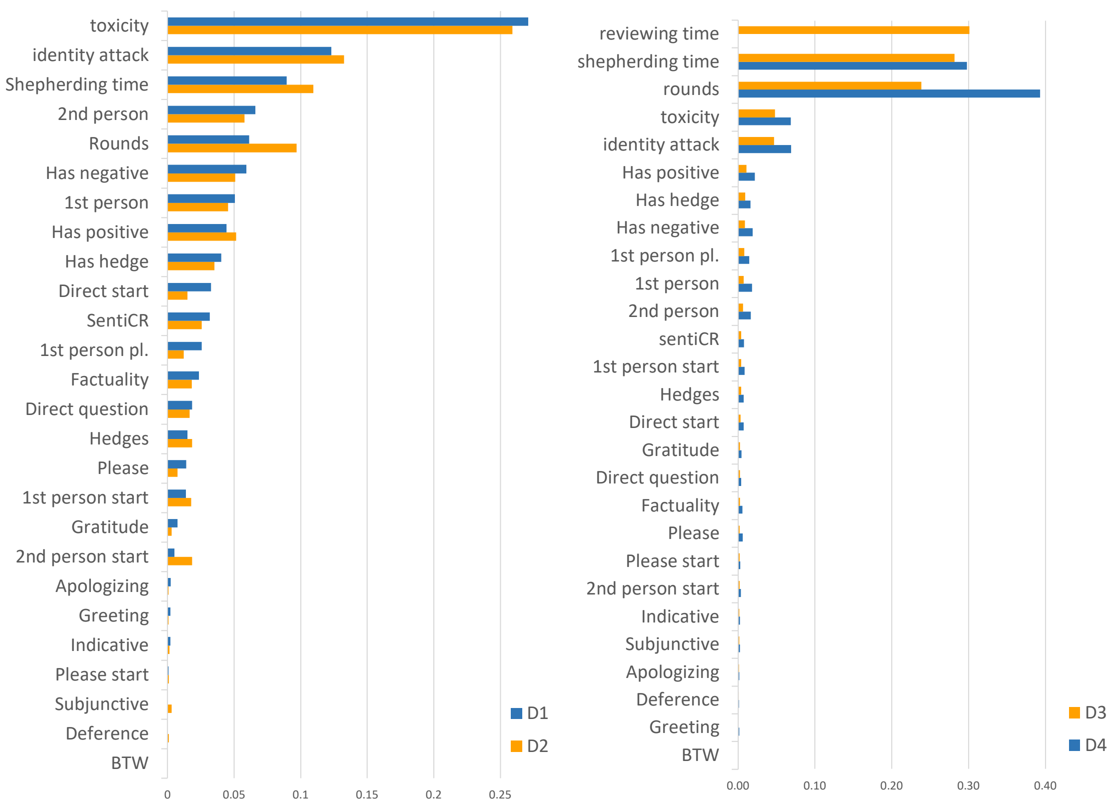


Figure 4.5: Logs-based classifiers' feature importance



(a) Toxicity (D1 and D2) (b) Pushback (D3 and D4)

Figure 4.6: Combined classifiers' feature importance

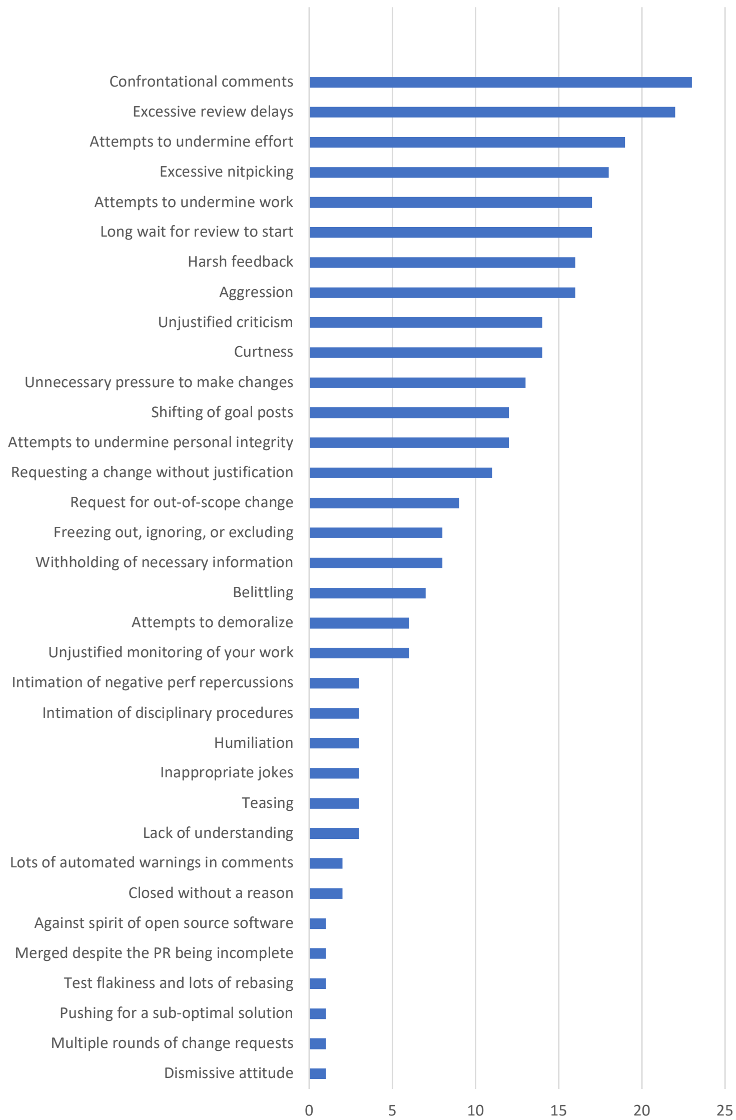


Figure 4.7: Reasons for pushback in OSS

Chapter 5

Intervention: A Dashboard for Maintainers

This chapter presents Climate Coach, a dashboard that helps open-source project maintainers monitor the health of their community in terms of productivity and inclusion. Through a literature review and an exploratory survey (N=18), we identified important signals that can reflect a project's health, and display them on a dashboard. We evaluated and refined our dashboard through two rounds of think-aloud studies (N=19). We then conducted a two-week longitudinal diary study (N=10) to test the usefulness of our dashboard. We found that displaying signals that are related to a project's inclusion help improve maintainers' management strategies.

5.1 Introduction

Open-source software (OSS) infrastructure is ubiquitous and vital to our daily life, powering applications in virtually every domain [2]. Economists refer to OSS as the "digital dark matter" to reflect its invisibility and importance and report its valuation in the billions of dollars per year [295]. To maintain this digital infrastructure, a constant supply of effort is necessary. Therefore, attracting and retaining contributors are of utmost importance.

However, many studies have found many challenges in making contributions to OSS projects and retaining contributors. On the one hand, there is a rich body of scholarly works on the barriers new contributors face. Surveying 20 studies on newcomers' barriers, Steinmacher *et al.* [296] compiled a list of 15 barriers that can be categorized into five groups: social interaction, newcomers' previous knowledge, finding a way to start, documentation, and technical hurdles. Some examples of barriers are not receiving an answer, lack of technical experience, and lack of documentation.

On the other hand, there are studies and grey literature reflecting the difficulties experienced by maintainers [43, 44, 45]. High volume of requests [44], unfriendly or even aggressive tones are also a source of burnout [46], making projects hard to attract and retain contributors.

This study presents a dashboard that intends to help maintainers monitor their community health in terms of diversity and inclusion. We define a healthy community as a community that is *friendly and inclusive*. Our dashboard consists of metrics calculated based on trace data recorded by GitHub.

The theory underlying our dashboard is signaling theory, which has a history of more than half a century in other fields of studies, such as economics [85] and biology [87]. It explains a scenario where a receiver, the party that is less informed of the situation, makes decisions based on the signals provided by the signaler, who has access to all the information. Signals can be any observable cues that indicate an unobservable quality of the signaler [109].

Online social coding platforms, such as GitHub, record and display various user activities. Such *transparency* offers users the opportunity to observe other users or projects. Dabbish *et al.* [26] reported that people make various types of inferences based on visible signals on GitHub. Qiu *et al.* [88] compiled a list of signals that can help new contributors select a more suitable and friendly project to contribute to. Trockman *et al.* [27] showed that badges displayed on projects' README have high signaling value in reflecting a project's quality. The value of signals are also demonstrated in many other studies, such as which repositories to watch [121], which pull requests (PRs) to accept [97], which developers to follow [122, 123], and which developers to recruit [110, 124].

While there are many studies reporting useful signals, not all of them are easily visible. Among the signals compiled by Qiu *et al.* [88], some important signals are less visible. For example, many studies point out the that impolite language is among the biggest barriers faced by newcomers [297, 31] and one of the causes of contributors' negative feelings [88, 89]. However, it is unfeasible for maintainers to monitor all conversations to detect unfriendly messages. With the help of natural language processing (NLP) tools, such as Perspective API,[1] our dashboard can flag comments that are potentially problematic and may need further investigation from the maintainers.

Moreover, there are signals that maintainers can get a rough idea based on observation but require data mining to obtain a more accurate count. For example, Egelman *et al.* [47] presented the idea of *pushback*, which refers to maintainers' behavior of blocking a code review. Egelman *et al.* [47] and Qiu *et al.* [89] found that pushback can be detected by the number of comments and the amount of time on reviewing and shepherding in both corporate and open-source settings. While one can count the number of comments in code review conversations, the amount of review time and shepherding time is less directly observable. In addition, it can be difficult for maintainers of big projects to spot conversations with the most comments or have taken longer than usual to review.

In addition to reflecting a project's status, our dashboard also provides "coaching" to maintainers by presenting validated effective maintenance strategies from prior studies. Although there exists plenty of scholar papers on contributors' barriers and validated methods of improving project management, they need a channel to reach practitioners. Our dashboard provides tips and validated results from prior studies to help maintainers improve their management strategies.

In summary, our study presents Climate Coach, a dashboard that aims to help maintainers improve their OSS projects' diversity and inclusion. As illustrated in Fig 5.1, our study is comprised of three major phases. **Phase 1** (Section 5.3): Email interviews with OSS maintainers to find out their strategies to handle new contributors. Literature review to find

[1] https://perspectiveapi.com/

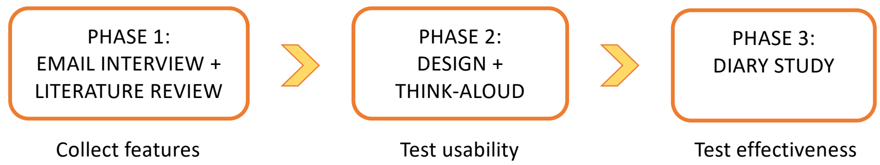


Figure 5.1: Study process

out metrics that can reflect a project's culture and inclusion. **Phase 2** (Section 5.4): Informed by the findings from Phase I, we designed a dashboard and iterated the design through two rounds of think-aloud interviews. **Phase 3** (Section 5.4.3): Two-week diary study with OSS maintainers to test the usefulness and effectiveness of our dashboard. Our results show that our dashboard can improve maintainers' confidence in supporting community health.

5.2 Related Work

In this section, we review literature on OSS project health and dashboards for teamwork. In order to design our dashboard to help maintainers assess project climate, during Phase 1, we performed a literature review to collect potential features and conducted email interviews with maintainers to finalize our feature selection. Our climate coach dashboard concerns mainly on healthy interactions among open-source contributors. Therefore, our literature review focuses on prior studies related to open-source collaboration, communication, and management. We discuss the list of features we identified from literature in Seciton 5.3.1. The rest of this section presents literature review on

5.2.1 OSS project health

While there are many prior studies on OSS project health, many have focused on the technical aspects, such as code size and release. For example, Goggins *et al.* [298] define open source project health as "a project's ability to continue to produce quality software." Goggins *et al.* [298] summarized that an OSS project's health can be measured via factors such as community growth, financial resources, software management, and a project's resilience to risks.

Some studies use project growth as a measure of health, *e.g.*, team growth, commit growth, comment growth [299], and turnover ratio [12].

There are also studies that define project health based on a project's success [300]. Metrics such as documentation, code quality (in terms of metrics such as structureness and efficiency), downloads, and user rating, are proposed to measure a project's health [300, 301]. Similarly, productivity, such as commit count, is also used as an indicator of project health [12].

Distribution of contributions among the community is also used as an indicator of project's health. For example, Aman *et al.* [302] use the Pareto principle to measure a project's health, *i.e.*, roughly 80% of the code being contributed by 20% of the contributors. Bus factor, *i.e.*, the risk associated with losing the key contributors and the knowledge that they possess, is also used as a health indicator [303, 304]. The assumption is that healthier projects have more evenly distributed contribution, where work is not centralized among a small set of individuals but spread across many individuals.

Our dashboard cares more about contributors' community health, with a focus on the community's culture, such as friendliness, responsiveness, and share of newcomers. We use signals that contributors use when assessing projects to join [88]. Since prior work showed that diversity can improve a project's productivity [12], by fostering diversity and inclusion, our dashboard can in turn have positive effects on the project's output.

5.2.2 Dashboard for team management

We took inspiration from other dashboards for team management, such as for more inclusive online meetings and improving teamwork skills.

Samrose *et al.* [305] created MeetingCoach, a wireframe dashboard, to facilitate more inclusive online meetings. They first conducted an initial survey, from which they collected feedback on what features can help create a more inclusive meeting, such as speaking turns. Then they created a wireframe and iterated on the design with interviews and think-aloud studies with in-situ meetings. Their dashboard improved meeting attendees' awareness of meeting dynamics that have implications for inclusion.

Ahuja *et al.* [306] built a dashboard to help college students build teamwork skills. This dashboard collected interactions from students using online platforms to perform team tasks, analyzed these data, and presented information about team and team member behaviors in real time, such as frequency of information exchange, number of words exchanged, and psychologically analysis on their conversation contents. They tested the dashboard with a freshman college class. They showed that displaying data collected from students' interaction can help instructors understand and support teams in their class.

Perrie *et al.* [307] proposed an interactive visualization tool, City on the River (CotR), for visualizing collaborations over time. This tool displayed contributions and products of a team on a timeline and enabled various analyses of team performance and collaboration patterns. They assessed CotR in GitHub projects by comparing outcomes between a team that used CotR and a team that did not use CotR and found that CotR may be more applicable for qualitative assessments than numerical analysis.

Biehl *et al.* [308] built FASTDash, an interactive visualization that try to improve team activity awareness through user-centered design, including surveys, team interviews, and in-situ observation. FASTDash focused more on team activities with shared workspace elements rather than interactions among team members. It used a spatial representation of the shared code base to highlight team members' current activities, such as which files were being viewed or which team members had source files checked out.

There are studies that are more relevant to the context of OSS projects. CHAOSS (Community Health Analytics Open Source Software) devised a list of metrics that can measure an OSS project's health and sustainability focusing more on a project's activity, productivity, and competitivity [298]. Guizani *et al.* [309] designed a dashboard with suggestions to help maintainers grow their projects, *e.g.*, adding "newcomer-friendly" labels, and retain contributors, *e.g.*, adding "rising contributor" badge. However, they focus less on communication and interaction among individual contributors. Our dashboard places a higher emphasis on signals that can reflect healthy communications in an open-source team with a goal to build a more inclusive culture.

5.3 Phase 1: Collecting signals

This section describes the first phase of our study (see Figure 5.1 for an overview).

During Phase 1 of our work, we conducted a literature review as well as a brief email interview with maintainers to learn about what signals would help maintainers improve their projects' diversity and inclusion. Our goal was to determine what signals could be included in our dashboard to assist maintainers in monitoring their project's health. We were interested in what strategies maintainers employed to manage newcomers since this is a significant burden on maintainers but also an important source of community growth and influence on how inclusive and welcoming a project seems to outsiders. The list of signals we identified from the literature review and survey is in Table 5.2. Since the literature is massive, we conducted an email interview to help us select more useful signals to include in our dashboard. In the rest of the chapter, we use *conversations* to refer to issues and/or pull requests (PRs).

5.3.1 Literature review

We reviewed published papers on topics related to OSS diversity and inclusion, newcomers, and communities. We compiled a list of signals that could be operationalized from prior study results in Table 5.2.

Responsiveness

Based on our literature review, for signals reflecting responsiveness, we included `the amount of time to close a conversation` and `the number of comments`. Delay in code review and excessive rounds of reviews are found to be associated with contributors' negative feelings [47]. Steinmacher *et al.* [310] found that not receiving enough help is one of the barriers new contributors often face.

We also included `the number of conversations closed without any comments` because prior studies found that conversations closed without comments is among the reasons why contributors leave an OSS project [310, 105]. Jamieson *et al.* [311] pointed out that it is because contributors felt their needs were not addressed properly, especially in value-related discussions [311].

Conversation tone

Plenty of studies have presented the harmful effect that unfriendly, impolite, or even toxic language can bring to an OSS community [297, 46, 312, 313, 89]. Our dashboard uses the Perspective API[2] to rate every comment in all conversations and flag the ones with high toxicity score or identity attack score.

[2] perspectiveapi.com

Moreover, Citron *et al.* [314] identified three ways to respond to toxic language or hate speech: removing the content, rebutting the content, and educating and empowering community users. Although our dashboard cannot perform the first two responses, we can point maintainers to potentially `problematic conversations` so that they can take actions.

Gamification

Simply displaying the focal project's signals does not provide maintainers a sense of how well they are doing, unless we provide them with standards or use other projects' performance as a reference. Goggins *et al.* [298] pointed out that comparisons with other projects can provide maintainers a sense of "how things are going." Therefore, our dashboard compares the focal project with four other similar ones on multiple signals. This can not only provide them a reference of how they are doing, but also encourage them to improve their projects' signals. We first decided to choose the four comparison projects for the maintainers based on the project's topics and its level of popularity. When we later conducted the diary study, we asked participants to choose the projects they wanted to be compared with.

Diversity

Signals that can reflect the diversity of the community would be helpful for maintainers. Based on Terrell *et al.* [7]'s finding that women might face lower PR acceptance rate, Goggins *et al.* [298] listed "Gender Bias - Ratio of female to male contributions accepted" as an indicator of health of project culture. However, we did not include gender diversity as a dashboard signal because GitHub does not record contributors' gender and we cannot accurately identify them either. Name-based gender inference technique, the most commonly used technique, supports only binary gender and does not have a perfect accuracy [315, 72]. We did not want to assign potentially inaccurate gender to individual contributors.

5.3.2 Email interview

We sent a short one-question email to maintainers asking about what they think about new contributors. We used GitHub API to identify 100 projects that had commits in the past week and owners that displayed their emails on their profile pages. Projects with fewer than three people were excluded because small projects are more likely to be personal or private projects rather than open sourced and less likely to have dealt with newcomers or contributions from nonmembers. We sent out 100 emails and got 18 replies. When selecting projects, we also try to recruit projects with different sizes and whether the project has women in their team, if the team is small, or among their top 100 contributors, if the team is large.

We sent maintainers in our sample an email asking *what their project thinks about new contributors*. Instead of directly asking what have they done to attract new contributors, we decided to ask this broad question so as not to lead on the project owners. The break down of responding projects in terms of size and diversity are shown in Table 5.1.

Table 5.1: Survey responses

Participants	Number of Contributors	Owner of a gender diverse project?
R0P1	298	N
R0P2	7	N
R0P3	21	Y
R0P4	21	Y
R0P5	200+	Y
R0P6	50	N
R0P7	34	N
R0P8	6	N
R0P9	4	Y
R0P10	8	N
R0P11	5,000+	Y
R0P12	47	N
R0P13	1,000+	Y
R0P14	3	Y
R0P15	1,000+	N
R0P16	200+	Y
R0P17	27	N
R0P18	96	N

5.3.3 Data analysis

We conducted thematic analysis on the responses we received from maintainers [316]. As a validation on our literature review, we focus on the themes that emerged from our literature review while paying attention to new themes. We first identified instances of different themes in the first ten responses. For each response analyzed, we identified owners' attitudes towards new contributors and actions they described taking to handle new contributors. Based on the themes we identified from our first round of open coding, we developed a set of initial codes and then continued open coding the rest of the responses, comparing each response with previously examined ones, adding new codes when a new theme emerged, and grouping codes to form higher level categories. When possible, we assign codes to categories we identified from the literature. We repeatedly discussed the codes and categories in a highly collaborative and iterative process.

5.3.4 Results

Overall, the projects in our sample welcomed new contributors while at the same time admitting that new contributors imposed a cost in terms of the effort required to manage contributions and socialize them. As one owner concluded, "*I welcome newcomers, but fear* *them.*" We grouped themes we identified from the emails into the same categories we found in the literature: responsiveness, conversation tone.

Responsiveness. Our email interviews confirmed the importance of Some maintainers pointed out that **fast reply is an important signal** because ignoring contributions (even bad ones) may create ill will (R0P1) and contributors may "*feel spurned*" (R0P2). Some owners told us they tried to signal their accessibility, for example, by providing a Slack channel or Twitter handle in the README, or changing their profile status to be "**Merging your PR**" (R0P2).

Conversation tone. Some maintainers mentioned that they try to show friendliness to newcomers, to encourage contributions (R0P15), and to signal inclusiveness (R0P4). They hope that the users of their libraries would feel welcome to contribute to it (R0P10). Some maintainers noted that they "respect new contributors' bandwidth and often help them to refine contributions collaboratively" (R0P4) by **commenting back and forth** on a design in a GitHub issue (R0P1). Some maintainers keep a **Code of Conduct** so that "*potential contributors have the feeling of a safety net*" (R0P10).

Valuing and recognizing newcomers. Some maintainers publicly recognize newcomers' efforts. Some maintainers put **newcomers' names to a contributor list** in the README (R0P1). Some invite contributors to become maintainers of the project and recognize their contributions (R0P5).

Onboarding material. Another way that maintainers try to welcome newcomers is to provide **beginner's guide or relevant documentations**. Some of the actions they took to welcome newcomers include providing **onboarding materials** "to show them the entire journey" (R0P6). Some mentioned the use of **a contributing guideline and issue tags** (R0P1). Nevertheless, they also mentioned that the use of "newcomer-friendly" tag was not very practical, because many of the issues were not newcomer friendly (R0P1). Some maintainers recognized the importance of documentations but also admitted that their testing process was not well documented, which may scare away potential newcomers (R0P10). *However, we did not include these in our dashboard because GitHub's Insight page consists of a checklist of all these recommended documentations.*

Contribution process management. Maintainers varied in their internal coordination processes or methods to manage teams, and these activities influenced how they in turn tried to help newcomers. Some tried to use **continuous integration (CI)** tools to automate the process and save maintainers' time (R0P1 and R0P11). They tried to speed the process by having **bots** to check if the submission has passed CI before notifying owners to review. However, at the same time, they also admitted that using an "*CI can introduce too many rules and conventions newcomers need to learn, which can be discouraging*" (R0P11).

5.4 Phase 2: Design and Think-aloud Studies

Based on the signals we identified from Phase 1, in Phase 2, we developed initial prototypes of our dashboard and used them to conduct two rounds of usability interviews with maintainers. In **Round 1**, we built our dashboard as a **GitHub issue** with the signals listed in Table 5.2, and conducted interviews with 9 maintainers. Then, in **Round 2**, based on the feedback,

Table 5.2: Dashboard signals and their references.

Category	Strategy	Reference	Dashboard signal
Team management	Team growth	Email	`Number of new contributors`
			`Number of active contributors`
Responsiveness	Fast response	[47], Email	`Average Close Times`
	Provide help	[310, 105, 311], Email	`Average Num Comments for Closed Conversations`
			`Number of issues or PRs closed`
			`Number of issues or PRs still open`
			`Num Conversations Closed with 0 Comments`
Conversation tone	Toxic conversation	[297, 46, 312, 313, 89], Email	Perspective API
			`Problematic conversations`
Gamification	Compare with peers	[298]	`Comparison to Similar Repositories`
		Added in the second version	
Social capital	Bonding social capital	[103]	`Recurring Contributors`
			`Avg months experience`
	Bridging social capital	[103]	`Number of new contributors`
Negative feelings	Excessive rounds of reviews	[47, 89]	`Open conversations with the most comments`
	Long shepherding time	[47, 89]	`Conversations that have been opened for the longest time`
Team management	Team growth	Email	`List of new authors`
			`List of active authors`
Contribution management	Label	R1P1 and R1P4	`Labels used in conversations`

we reformatted the dashboard from a GitHub issue to a **web page** along with some other adjustments, and conducted additional interviews.

5.4.1 Round 1: Initial Prototype as a GitHub Issue

We initially designed the climate coach dashboard as a GitHub issue (see Figure 5.2 and 5.3). Our dashboard contains four types of signals: ① *summarized*: showed the average of measurements in the past month; ② *temporal*: presented the trends of some signals in the past half a year; ③ *indicative*: linked to potentially problematic conversations, and ④ *comparative*: showed how the focal project compared to similar projects.

Summarized signals: Repository's basic statistics in the past month The section, `Basic Stats`, displays signals from the Community and Responsiveness categories shown in Table 5.2.

It includes `the number of new contributors` and `the number of active contributors` in the past month. For responsiveness, the dashboard reports `the number of issues and PRs closed` in the past month and `the average close time of issues and PRs`, as well as `the number of open issues and PRs` and the `average time they have been open`.

Temporal signals: Trends in the past half a year This dashboard provides plots of the trends of signals shown in the basic statistics section as a context of how their projects have developed

Indicative signals: Conversation tone analysis Inspired by a study by Raman *et al.* [46] and Qiu *et al.* [89], we added a signal for conversation tone. We use the Perspective API to get a toxicity score of issues, PRs, and their comments posted in the past month. We report the number and the rate of posts with a toxicity score > 0.5 as "potentially inappropriate."

Comparative signals: Comparison with other projects We compare the project with other similar projects on the signals shown in the `Basic Stats` section. We identify comparable projects by the range of stars and topics set by projects.

Think-aloud Studies with Maintainers

We designed a detailed semi-structured interview and think-aloud protocol to test the usability of our dashboard and guide later stages of development. We also used this opportunity to better understand how maintainers assess their community health and approach issues related to diversity and inclusion. Section 5.8 presents our interview protocol. We used real data from their repositories in the interviews. Each dashboard presents basic stats and links to conversations of the past month and trends of the past half a year.

Recruitment To recruit participants, we searched on GitHub for a stratified range of stars, which serves as an approximation of a project's popularity. Our participants' projects have stars ranging from 11 to 20.6K. We also filtered projects based on the number of contributors (> 20) since our dashboard can only be useful when there are activities.

We contacted the project maintainers, *i.e.*, owner of the project or the top two contributors if they provided emails or Twitter handles on their GitHub page and the project has recent activities. Although we strived to recruit women maintainers, we did not succeed due to the low representation of women among maintainers. In the end, we interviewed 10 men maintainers for our first round. We refer to each of them as R1Px from now on. The information of each maintainer and their projects is in Table 5.3.

Protocol After collecting participants' verbal consent for recording audio and video, we started the interview by asking about the maintainers' backgrounds and roles in the projects. Our interview protocol consists of two major parts. During the first part, we asked participants questions regarding their project community, their perception of the health of their communities, and their methods of managing their communities.

The second part adopted the think-aloud approach to understanding how participants use the dashboard. Before the interview, we generated an individualized dashboard for each participant with their repository. We asked the participants to browse through our first design of the dashboard (Figure 5.2 and 5.3) and speak out any thoughts that crossed their minds. If they had any questions during the think-aloud, we answered them after they finished browsing the dashboard. After participants finished browsing the dashboard, we asked participants several follow-up questions, such as signals that they considered important, signals that should have been there, and signals that were less important or unnecessary.

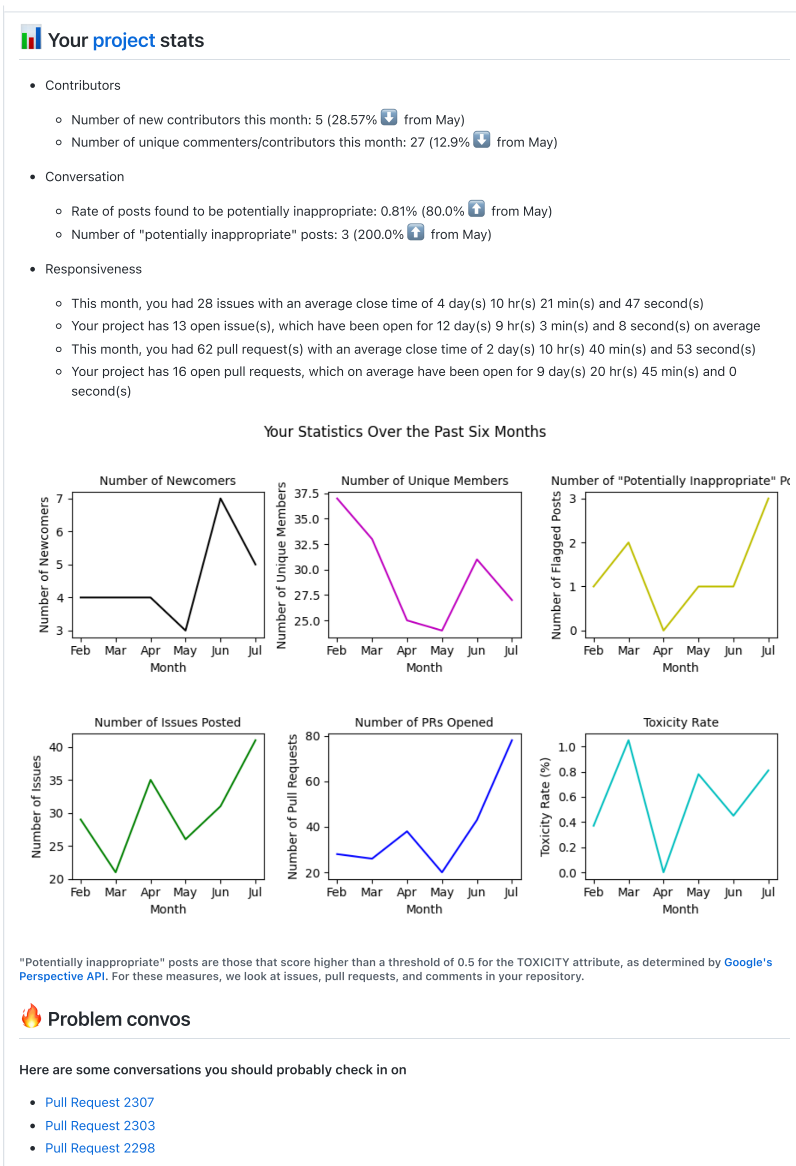


Figure 5.2: First iteration of design: Basic statistics.

Data analysis There are two goals of our coding: one is to understand maintainers' understanding of community health; the other is to identify feedback to our dashboard. We first performed open coding on interview transcripts. Two of the authors first coded two interviews independently. Then they met to discuss their codes through a constant comparison method: they consolidated codes into a shared set of codes by combining overlapping codes or developing new codes. The two authors coded another four interview transcripts independently with the preliminary code book before convening again to discuss the generated codes. We continued conducting interviews while coding the transcripts and concluded the first round of interviews when we reached theoretical saturation, *i.e.*, no new themes emerged from new interviews. After the two authors coded the rest of the interviews, they met again to discuss all the codes and coded paragraphs. Then the two authors conducted axial coding on the full

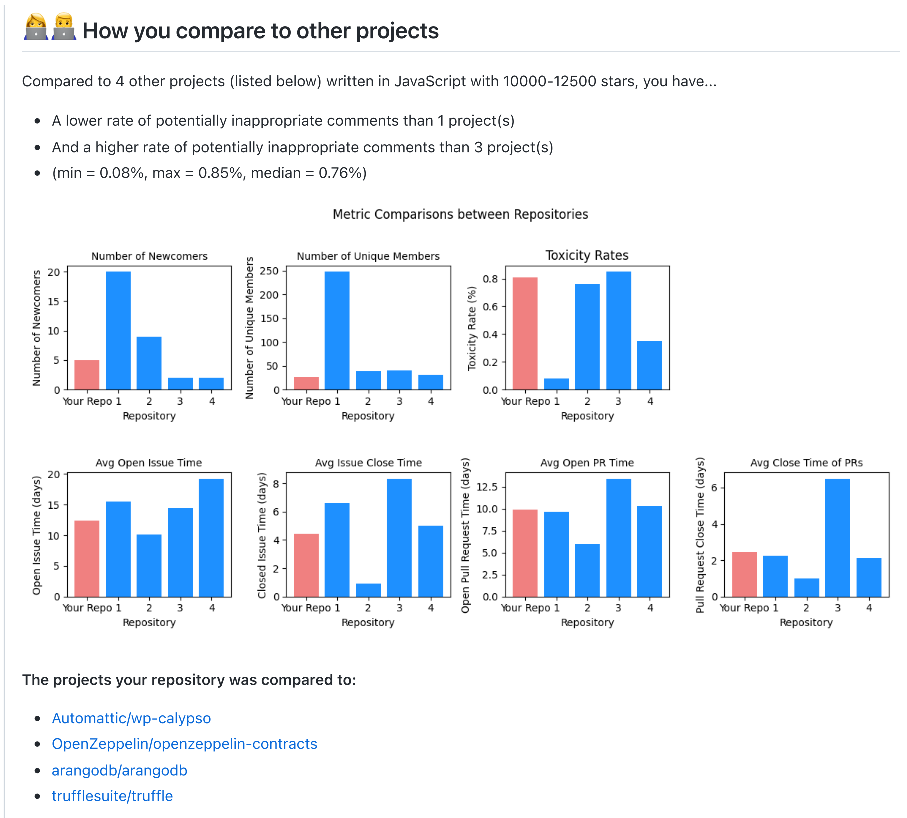


Figure 5.3: First iteration of design: comparison to other projects.

set of codes: we considered the relationship among the codes and merged them to develop a set of higher-level categories.

Results

Before we conducted the think-aloud activity, as a confirmation/alignment of thoughts, we asked participants about their understanding/definition of project health and their attitudes towards diversity.

Perceptions of Community Health When asked about criteria of community health, similar to our findings in prior studies [300, 301], many maintainers thought of technical aspects. For example, R1P3 mentioned continuous integration (ci) as an indicator of community health, including "*how often is it being overwritten*" and "*build times*" (R1P3).

Usage is also mentioned as a health indicator by several maintainers (R1P2, R1P6, R1P9, and R1P10). R1P2 told us they cared about their customers and the types of projects that depend on them. R1P9 also told us that they cared about their project's application. R1P6 and R1P10 both said that they considered the number of downloads as a health indicator.

Some participants considered maintainers' responsiveness as a health indicator (R1P1, R1P4, R1P5, and R1P6). When looking at the summary of the `number of comments`, R1P4 pointed out that having good commentary indicates good health. These points of view echoed the findings by Steinmacher *et al.* [296] that barriers newcomers face include the lack of responses from maintainers. While admitting that maintainers can be busy with other things, R1P5 said they "*try to find maybe an hour to a day to help people with troubles*" or "*try*

Table 5.3: Information of the Participants from the 1st Round of Interviews

Participant ID	Number of stars	Project size
R1P1	11	13
R1P2	67	28
R1P3	5.7K	42
R1P4	20.6K	147
R1P5	468	27
R1P6	1.5K	39
R1P7	468	27
R1P8	176	37
R1P9	65	24
R1P10	810	17

to answer some questions, on the slack." P1 even set a strict timeline of getting a response within one or two days,

> "*I can go into GitHub, open an issue for something that's not working or add a feature request for something I need inside of that particular project, and typically within like 24-48 hours, I'd get a response, that's something I'd call a healthy project with a nice reactive maintenance team, as well as a community there, ideally*" (R1P1).

Several participants mentioned contributors' sustained participation as an indicator of community health (R1P2, R1P3, R1P4, R1P5, R1P6, and R1P9). Concerning contributors' sustained participation, P4 pointed out that the `number of new contributors` indicates that their community is growing, which is a good sign. R1P2 also mentioned that the way they build their community is "*by engaging with groups of students who are going to implement new standalone tools that might be published as separate packages.*" P9 commented on the same point, "*one big thing in terms of the developer community is like, [...] how do we figure out things that make people want to contribute and want to keep working on the project?*"

Another type of health indicator is the help maintainers can provide to the community. Help includes maintainers' response to issues or pull requests (R1P2 and R1P9), documentation (R1P1, R1P4, and R1P9), and office hours (R1P1, R1P5, and R1P9). P2 acknowledged that " *a really bad way to ruin a community is by ignoring pull requests.*" He further commented that the `number of pull requests that are still open` "*should probably be zero unless there is a culture in a particular project which means that they're gonna have a bunch of long-standing pull requests.*" P1 commented that one thing he "*hate[d] on other projects is not having a good documentation,*" although he also acknowledged that "*unfortunate in that regard and we just don't have the resources to go back and document everything.*" R1P1's comment reflects a dilemma shared by some maintainers that they are aware of the best practices, but they are unable to fulfill them.

R1P1, R1P5, and R1P9 all mentioned that a healthy community should have "*scheduled office hours that happen on a regular basis*" (R1P1) so that contributors "*can get help*" (R1P9).

R1P5 summarized it as contributors can "*get any information and get any kind of help in this community.*"

Attitudes towards Diversity and Inclusion When asked about diversity, some commented that it is hard for them to know the level of diversity in their community (R1P6 and R1P10) because "*generally the only thing I see is their GitHub username*" (R1P6).

Although some maintainers admitted that they cared about diversity and even desired more diversity (R1P1, R1P2, R1P4, R1P5, and R1P6), they are limited by their environment. For example, P1 told us that "*in <country> there's not a lot of diversity [in terms of race and ethnicity],*" especially since they mostly hire locals "*in a small town that's 70,000 people.*" Hence, most of their members are white males. This idea is shared by R1P10, who listed several countries he interacted with and felt the ratio of women was lower than in some other countries. On the contrary, being in a university, R1P2 experienced several occasions "*where all the students who were working on the project in [their] group were all women.*" When there is a lack of demographic diversity, maintainers consider diversity as a diversity of thoughts (R1P1).

Maintainers have generally taken action to improve the diversity of their community (R1P3, R1P4, R1P6, and R1P8). For example, with about 20,000 followers on Twitter, P6 tried to advocate diversity on social media. Some try to "*sourcing people from different paths to provide programs to help educate people into the space better*" (R1P4). Several participants told us they try to improve diversity by being welcoming (R1P3, R1P4, R1P6, and R1P8).

Feedback on the Dashboard We report feedback to our dashboard and our adjustment in the next section.

5.4.2 Round 2: Dashboard as a web page

Based on the findings from the interviews, we created a revised version of the dashboard.

Changes on the format

Web version Instead of a GitHub issue, the new dashboard is a webpage created using JavaScript and its `Chart.js` library. This change can avoid "off-putting" maintainers (R1P9) and address participants' requests for high resolution and interactive graphs (R1P2). In the default setting, we use line charts to display trends of `new issue authors`, `new PR authors`, `avg close time for issues`, `avg close time for PRs`, `avg comments to issues`, and `avg comments to PRs`. We added drop-down buttons on the sides to allow users to select other charts to display.

Highlight basic signals There was some confusion surrounding the wording of the text above the graphs in the initial report (R1P1, R1P4, and R1P6). As a result, the new version of the dashboard includes a simplified version of the signals above the graphs, including `new issue authors`, `new pr authors`, `avg month experience`, `recurring contributors`, `avg comments to issues`, `avg comments to prs`, `avg days to close issues`, and `avg days to close prs` (Figure 5.5). We also rounded the responsiveness signals to days, as suggested by participants (R1P3 and R1P6).

Alternative statistics Some participants from the prior round pointed out that, in addition to an average of the signals, which can be sensitive to outliers, they would also like to see the median of the signals (R1P3). Therefore, we added a drop-down button (`Avg/Median`) in each graph tab so that maintainers can choose between different measures. In addition, the drop-down menu also included alternative signals, such as the number of new contributors *vs.* the number of active contributors.

Links to authors In addition to reporting the number of new contributors, we also list out their logins under the tabs `New Issue Authors` and `New PR Authors`.

New signals

Interpersonal conflicts Egelman *et al.* [47] and Qiu *et al.* [89] reported that *pushback*, the perception that a reviewer is blocking a change request, can be detected by the long review time and excessive rounds of reviews. Inspired by the pushback study, we created a section called `Conversations that Need Your Attention` that includes links to open issues or PRs that have been opened for a long time or with many comments because these conversations might create negative feelings among contributors.

Social capital Inspired by Qiu *et al.* [103]'s work on how social capital influences contributors' engagement, we added signals related to bonding and bridging social capital. For bonding social capital, we computed the average tenure (in terms of months) of the active contributors in the past week (`avg month experience`). For bridging social capital, we computed the number of new contributors in the past week (`recurring contributors`).

Usage of labels We added a summary of how the project uses labels per requests by the round 1 participants. Several participants from the first round mentioned that they would like a more detailed report on issues and PRs (R1P1, R1P4, and R1P9). More specifically, they would like to see a "classification of the issues" (R1P1) because "not all issues are created equal" (R1P9), and they would like to find out "how many bugs are being open [...] versus enhancement requests" (R1P4). Therefore, we added a section (Figure 5.8) showing each label's number of issues and PRs created in the past month.

Reinforce inclusion goals After the first round of interviews, the dashboard only contained the open-source project's signals. However, Goggins *et al.* [298] described the importance of transparency and context with analytical signals. Therefore, we added `tips` throughout our dashboard to help maintainers improve their management strategies. These tips are displaying results from prior studies on OSS management strategies, such as avoiding pushback [47, 89] in code review and adding a Code of Conduct [82]. The full list of tips is shown in Table **??**.

Moreover, we added sections `Methods` and `References` (Figure 5.10) for transparency, so our users could see our sources and the way we created the dashboard. We also added `Prior Research Results` section (Figure 5.10) which included `Features Affecting Project Attractiveness` to provide maintainers actionable suggestions in addition to presenting numerical signals.

Think-aloud Studies with Maintainers

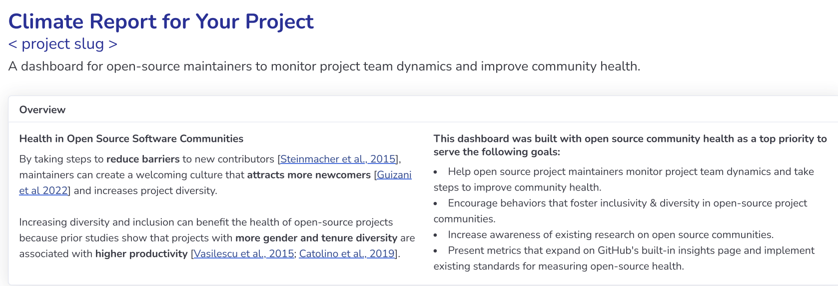


Figure 5.4: Version 2: Overview

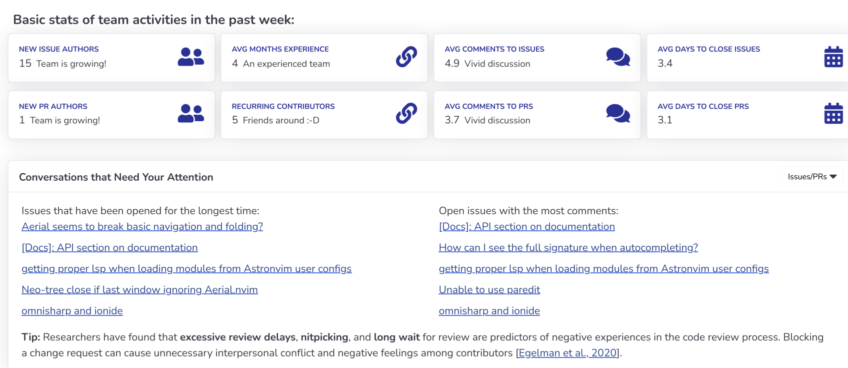


Figure 5.5: Version 2: Basic Stats

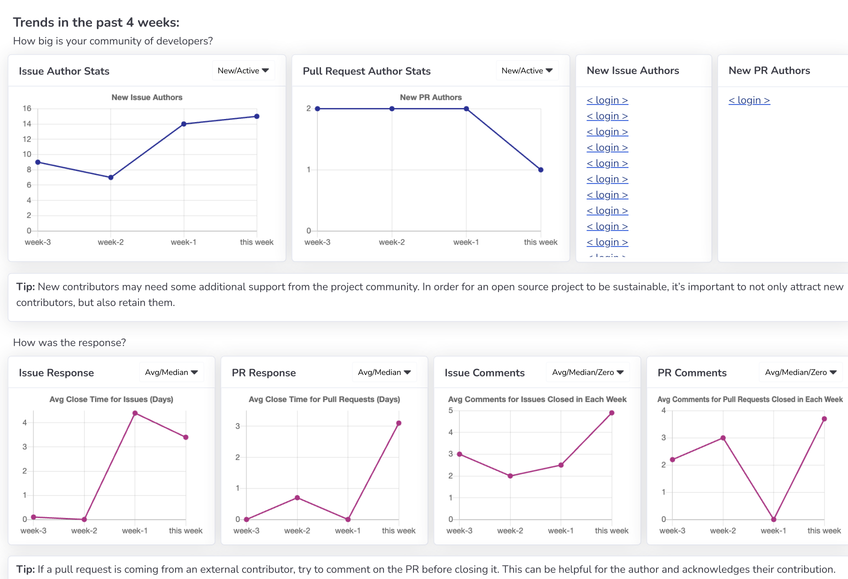


Figure 5.6: Version 2: Trends

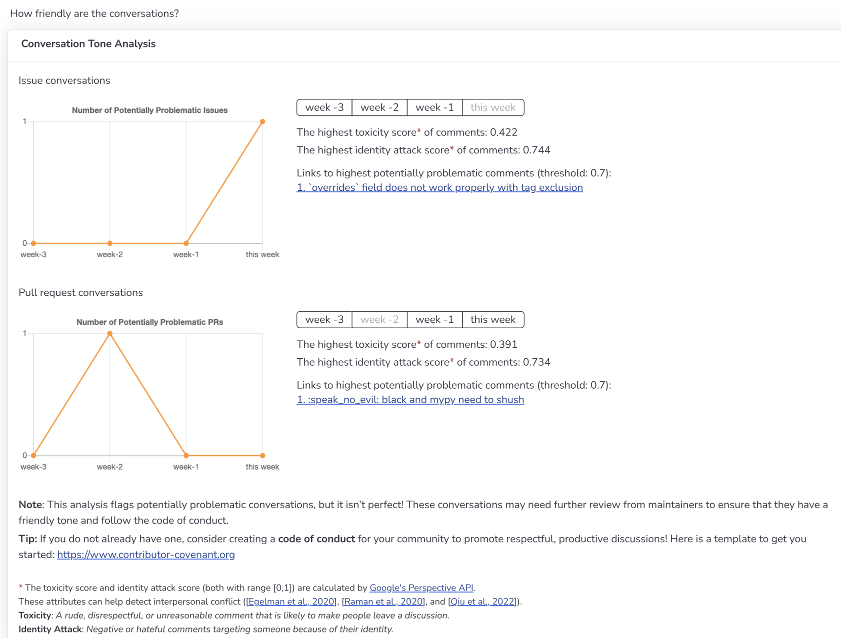


Figure 5.7: Version 2: Conversation Tone Analysis

Figure 5.8: Version 2: Labels Used by Issues and PRs

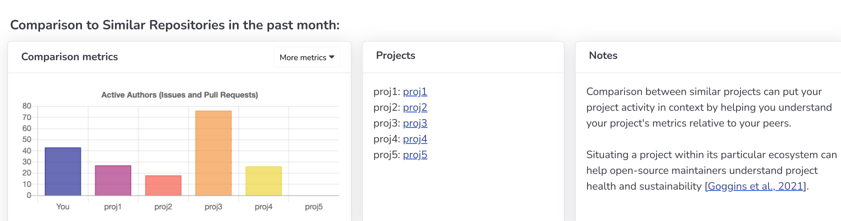


Figure 5.9: Version 2: Comparison

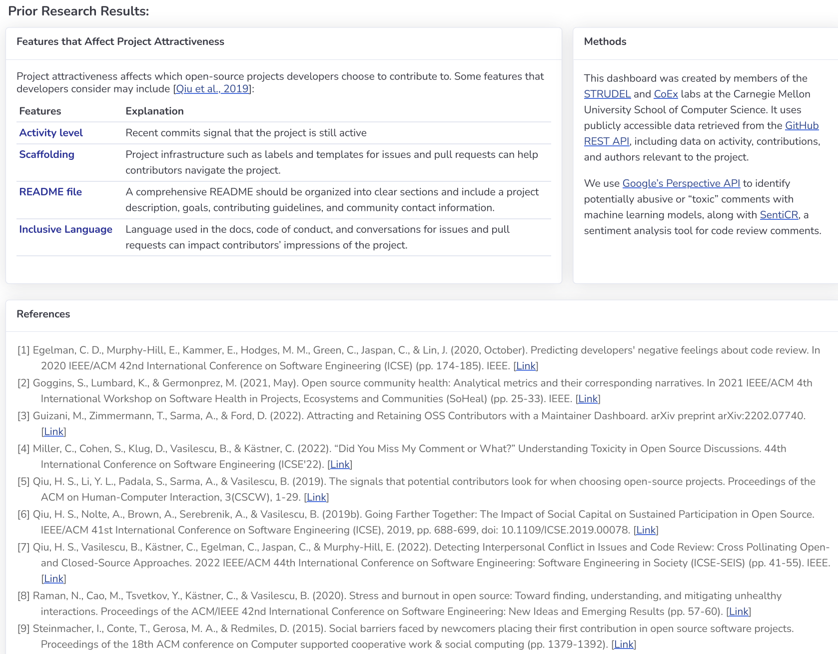


Figure 5.10: Version 2: Methods and References

Dashboard signal	Tip
`Conversations that Need Your Attention`	Researchers have found that excessive review delays, nitpicking, and long wait for review are predictors of negative experiences in the code review process. Blocking a change request can cause unnecessary interpersonal conflict and negative feelings among contributors [47].
`New authors`	New contributors may need some additional support from the project community. In order for an open source project to be sustainable, it's important to not only attract new contributors, but also retain them.
`PR comments`	If a pull request is coming from an external contributor, try to comment on the PR before closing it. This can be helpful for the author and acknowledges their contribution.
`Conversation tone analysis`	If you do not already have one, consider creating a code of conduct for your community to promote respectful, productive discussions! Here is a template to get you started: https://www.contributor-covenant.org
`Conversations by labels`	Consider adding issue labels that explicitly highlight starter tasks for new contributors. Labels like "newcomer friendly", "good first issue", and "help wanted" can help attract and retain new contributors [309]. These labels will appear in GitHub repository search results.

Table 5.4: Tips we provided in our dashboard

Table 5.5: Information of the Participants from the 2nd Round of Interviews

Participant ID	Number of Stars	Number of contributors
R2P1	544	18
R2P2	73.9K	100+
R2P3	708	100+
R2P4	131	27
R2P5	158	8
R2P6	2.1K	100+
R2P7	126	28
R2P8	8.3K	98
R2P9	2.1K	100+

Procedure

We conducted a second round of interviews to test the usability of our new design. We made slight modification to the protocol from the first round of interviews. Same as the previous round, we recruited maintainers of open-source projects on GitHub. We interviewed a total of 9 maintainers for the second round of interviews, who worked on projects within the range of about 100 to 80,000 stars and at least 20 contributors listed on GitHub. The summary of the participants' projects is shown in Table 5.5. We refer to each of them as R2Px in the rest of the paper.

Two of the authors coded the interviews in the same way as the first round, paying more attention to the feedback this time. As we conducted interviews, we coded the transcripts and made adjustment to our dashboard if multiple participants provided the same feedback. We concluded the second round of interviews when our dashboard features became stabilized.

Results

Below we summarize the feedback we received from the second round of interviews. Overall, most maintainers had a positive impression of our new design. Many of them pointed out several features that are useful for monitoring the community activity. At the same time, many of them pointed out improvements that could be made to our dashboard.

Feature Usefulness

Conversation analysis Three maintainers considered the conversation analysis to be the most important and useful feature of our dashboard (R2P5, R2P6, and R2P9). They found the tone analysis to be the "the big selling point" (R2P6) that could "be highlighted much earlier in your reporting" (R2P5). As R2P6 summarized, links to potentially problematic conversations were actionable items,

> "*[...] with these actionable things you know, you can go actually take some sort of action to address concerns and anything that has a negative sentiment. Try to squash right away and make it more straightforward*" (R2P6).

Potential pushback conversations Links to conversations with long open time or many comments were considered to be useful by many maintainers (R2P4, R2P5, R2P6, R2P7, R2P8, and R2P9). Although some maintainers told us that some conversations were left open on purpose (R2P8), others told us that those conversations were the "things [they] can look at and take action on" (R2P6) and would even like to "go and actually address these right now" (R2P7). R2P5 echoed the findings of pushback in code reviews, Egelman *et al.* [47] and Qiu *et al.* [89] pointed out that these conversations "can almost directly correlate potentially to anything that's, you know, negative" (R2P5). During our interview, the links even helped R2P8 identify a thread that waits for his reply while he thought he "was waiting for her reply there" (R2P8). As R2P6 nicely summarized, the links are

> "sort of a daily dashboard where I can say, Oh, you know here's my in-tray for the week. You know here's stuff that needs attention, here's stuff that may have fallen through the cracks, is something I need to pay attention to" (R2P6).

This feature is especially helpful for big communities. As R2P9, the maintainer of a project with 100+ contributors, told us that our links help them identify conversations that need immediate attention because "there are probably 50 parallel semi-active conversations going at any time, and [they] certainly can't track that" (R2P9).

The number of closed issues and PRs R2P4 told us that the number of closed issues and PRs is very useful because they are a research institute and they can put the data in their grant report:

> "Knowing the pull request stats are very valuable too. Like the new authors. That one probably would be the most useful for us as far as reporting to our granting agencies, and yearly reports where you just say like, Oh, this last year we closed like 300 tickets, and we opened like 6,000 or something" (R2P4).

Labels R2P6 and R2P7 mentioned that the numbers of issues or PRs under different labels are useful. R2P6 told us that they used "labels to categorize pull requests for the change log" so "these labels actually matter to us" (R2P6).

Average response time R2P7 told us that the average response time is a useful feature, especially he is overseeing many GitHub repositories. He said it could make him aware that "sometimes, [in] some repos, [...] people see [there is] an issue and no one even responds to it" (R2P7).

Dashboard Design Feedback and Changes

Goals There was some uncertainty about the title of our dashboard (R2P5) and the dashboard's purpose. Several interviewees mentioned they felt that this could be created by GitHub (R2P1, R2P6, and R2P7).

This feedback pointed out that our dashboard did not clearly convey its objective to maintainers. Due to this, we decided to add in an `Overview` (Figure 5.4) section that contained background and goals for the dashboard.

Formatting and Design Decisions We received several feedback on the formatting and certain design decisions, such as the use of colors and some features are missed by participants. We made adjustment when two or more participants pointed out the same problem.

Feature Suggestions Participants had a couple suggestions of interesting features they would like to have in a dashboard.

On a front-end functionality perspective, a few participants mentioned that they wanted a more interactive dashboard. One participant wanted to be able to drag the different dashboard sections around to customize it to their preference (R2P9). We could not address this feedback at the moment, but we did take note of which sections most maintainers felt were more important and should have been highlighted at the top of the dashboard, as noted in the Format Issues section above. Additionally, participants wanted to be able to change the date ranges for the data (R2P1 and R2P4) to have a better idea of how their project developed over time. Unfortunately, we were not able to add this feature at the moment.

5.4.3 Phase 3: Diary Study

After incorporating changes to the dashboard based on feedback from the second round of interviews, we further tested the dashboard in a two-week diary study [317]. We include the diary study protocol in Section 5.9

Procedure

After incorporating feedback from the second round of interviews into the dashboard, we designed the protocol for a longer-term user study for open source maintainers. This study lasted two weeks and followed the structure described in the graphic below, which includes an initial survey, onboarding session, weekly survey, and exit survey. Participants were compensated $50. Below we describe each of the study components in more detail.

Initial Survey + Onboarding Session (30 minutes)

Initial survey (20 minutes) We provided a Google form for participants to fill out. We also provided participants with the consent form and information about the study structure. In the survey, we asked for background information about the maintainer's identity, habits, and project dynamics.

The survey asked questions about *maintainers' workflow*, *their perception of their community's health*, and *projects they want to be compared with*.

When asking about maintainers' workflow, we asked about whether they are seeking for new contributors, the importance of increasing demographic or technical diversity, and how confident are they in managing their community. We also asked them to rate the priorities of several management actions, including "fast response time to issues," "fast response time to PR," "creating a welcoming environment," "attracting new contributors," and "attracting a diverse group of contributors." We then asked them how often do they respond to issues and PRs each week. We also asked them about their goals for your project community.

Then, we asked participants their understanding of community health. We asked three open-ended questions: *How would you describe your project's community health? How would you define diversity in open-source software? How would you define inclusion in open-source software?*

To make our comparison signals more useful, we asked participants enter projects they want to compare with. At the end of the survey, we asked them to sign up for a time slot for a Zoom call for the onboarding session.

Onboarding session - Zoom call (10 minutes) During the Zoom call, we explained the logistics of the study and weekly survey. Then we showed them the dashboard and ensured they understood the basic setup. We also answered any questions the participant has. Lastly, we established a social connection with the participant

Weekly usage (30 minutes each week × 2 = 1 hour total)

Participants could freely use the Climate Coach dashboard as little or as much as they want during the study. Each Friday, we sent an email asking participants to complete brief weekly surveys about how they used the dashboard that week. The survey itself took about 15 minutes; they also were expected to spend time looking at the dashboard. Participants were asked to complete the survey within 48 hours of receiving it.

The weekly survey consisted of two parts, *maintainers activity* and *dashboard engagement*. The questions in the maintainers activity portion included the types of contributions they receive, the amount of time they spent on maintaining, and the tone of conversations in their community. In the dashboard engagement portion, we asked participants questions regarding the usefulness of the dashboard, such as how often they checked the dashboard, which parts were most useful, which tips were more helpful, and how reliable were the signals.

Exit Survey (30 minutes)

After two weeks, we sent participants a survey with questions to get feedback on the dashboard and compare responses from the initial survey. We repeated questions from *maintainers' workflow* and *perception of their community's health* in the initial survey, and added questions regarding *the usefulness of our dashboard*. We asked them to rate their level of agreement with a list of statements regarding whether the dashboard is useful for them and other maintainers. To test if our dashboard has any effect on their management strategies, we asked if they made any changes after viewing our dashboard. Lastly, we asked them how likely were they going to continue to use this dashboard after the study ends. The survey concluded with an open-ended question for their feedback on the dashboard.

We provided 5-point Likert scales for participants to measure their level of agreement with statements regarding their perception of their community's health and the usefulness of our dashboard, with 5 being "strongly agree" and 1 being "strongly disagree". To test if they were paying attention to the statement rather than click "strongly agree" or "agree" for all statements, we reverse-coded some of the statements as an attention check. When analyzing responses to these statements, we first reversed the responses, *i.e.*, "strongly agree" as "strongly disagree".

Recruitment

For the diary study, we explicitly recruited maintainers from big and active projects. From the two prior interviews, we learned that big projects could benefit more from our dashboard (R2P1) because there is a number of things to keep track of that can exceed maintainers' capability. Moreover, since our diary study's survey frequency was weekly, less active projects would not have generated sufficient activities to appear on the dashboard. Therefore, for the

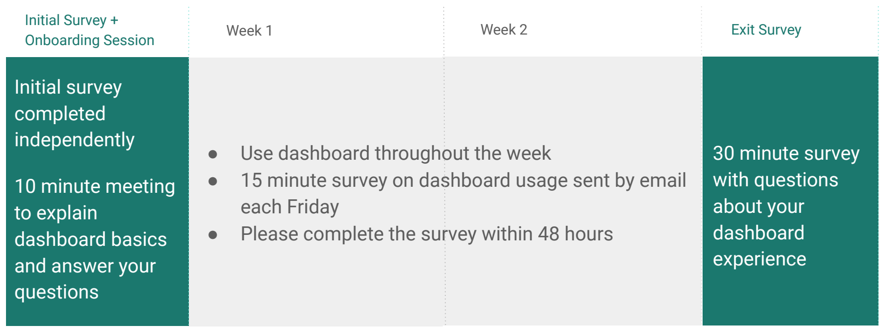


Figure 5.11: Diary Study Logistics

diary study, we searched on GitHub for projects with at least 1K stars, followers, or 100 to 200 forks.[3] From the search results, we picked the projects with activities (issues or PRs) within the last week and with at least 10 contributors. Similar to previous interviews, we contacted only the maintainers who left their emails or Twitter handles on their profile pages.

In the end, we recruited 10 participants for our diary study. Two of them reached out to us on Twitter. The rest of them accepted our email invitation. We sent out 128 emails, and 8 of them were accepted (respond rate 6.25%). The summary of all the participants' projects is shown in Table 5.6. We refer to each of the participants as R3Px below.

Data Analysis

We analyzed the responses to the 2 weekly surveys and the exit survey, using participants as the unit of analysis. One of the researchers performed open-coding on open-ended questions in the surveys. We affinity diagrammed codes generated from the open-ended responses to identify themes in participants uses of and reactions to the dashboard.

Results

Participant information

We recruited a diverse group of participants. Four out of ten participants were women. The years of experience ranged from less than a years to 10+ years (see Figure 5.12). Most of them were involved in more than one OSS project (M = 5.9, SD = 5.22). The projects also varied in terms popularity and team size (see Table 5.6). Three of the participants were the sole maintainer of their project, the rest were either one of the maintainers or a lead maintainer with other specialized sub maintainers.

Maintainer Workflow After viewing our dashboard, maintainers reported various goals that can be categorized into three groups: *expanding the community (R3P2 and R3P7)*, *accelerating response (R3P1, R3P3, and R3P7)*, and *improving communication (R3P5 and R3P7)*.

In both the initial and exit survey, we asked maintainers to rate the importance of five goals, including fast response and recruiting new contributors. Participants were asked to

[3]https://docs.github.com/en/search-github/searching-on-github/searching-for-repositories

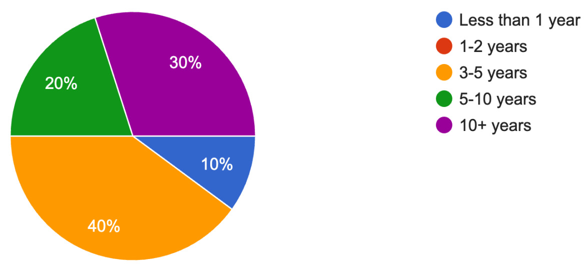


Figure 5.12: Years of Experience in Open-Source Contribution

Table 5.6: Information of the Participants from the Diary Study and Their Basic Stats during the Two Weeks

Participant ID	Number of Stars	Total Number of Contributors	Avg Issues Closed	Avg PRs Closed
R3P1	2.5K	31	4	8
R3P2	4.5K	47	32	14
R3P3	146	27	2.5	8
R3P4	8.1K	100+	26	118.5
R3P5	1.3K	19	0	2.5
R3P7	6.3K	26	2.5	0
R3P9	2.1K	93	0	19
R3P11	8.1K	100+	25	103
R3P12	18.7K	100+	5.5	15
R3P14	23	7	0	0

give a rating between 1 (lowest priority) and 5 (highest priority) for each of the five goals. We ranked the average ranking of all participants and found that the priority order of the five factors did not change between the initial and exit surveys. We suspect that the diary study duration was too short for maintainers' priority to change.

In both the initial and exit survey, most of the participants placed attracting new contributors as lower priority (initial: M = 3, SD = 1.22; exit: M = 3, SD = 1.26). Attracting a diverse group of contributors has an even lower priority (initial: M = 2.44, SD = 1.42; exit: M = 2.17, SD = 1.47). Tasks with the highest priority are fast response time to issues (initial: M = 3.78, SD = 1.20; exit: M = 4.33, SD = 0.52) and to PRs (initial: M = 4; SD = 1; exit: M = 4, SD = 1.10). They are followed by "creating a welcoming environment" (initial: M = 3.78, SD = 1.09; exit: M = 3.5, SD = 1.22).

Participants had extreme diversity on their frequency of responding to issues and PRs each week. Almost half of them indicated that they responded to issues and PRs 1-3 times per week whereas some other participants indicated that they responded 10+ times per week. We did not discover a clear difference between the initial and exit survey in terms of the frequency of responding to issues and PRs.

Dashboard feedback

Overall, most participants agreed that the dashboard was useful to them (M = 3.75, SD = 1.16). Except for 2 participants, the rest expressed that they would continue to use this dashboard after the study. Most of them agreed that the dashboard would be useful to most maintainers (M = 4.33, SD = 1.21).

Comparing participants' responses to the initial and the exit surveys, we found that after using the dashboard, participants became more confident in supporting the community and encouraging a healthy community. Overall, participants showed higher agreement with the statement *I feel confident in supporting the community of contributors in my project* (initial: M = 4.44, SD = 0.53; exit: M = 4.63, SD = 0.52). Three participants provided higher rating in the exit survey than in the initial one. The other participants provided the same rating in both surveys.

The exit survey also showed an improvement in the agreement with the statement *I am sure about how to encourage a healthy project community* (initial: M = 3.33, SD = 1; exit: M = 3.88, SD = 0.64).

While most participants acknowledged the usefulness of the dashboard, R3P7, the maintainer of a relatively small project commented that, because his project is not very active, the dashboard would be more useful if the signals were aggregated by month rather than week,

> "*My repository is quite small and not very active. Because of this, many metrics are empty or not precise enough. For example, Conversation Tone Analysis works by week. It would be more useful for me to see such statistics by month or by 6 months, since in a given week I can get only 1-2 comments anywhere, or none at all.*"

Useful signals In each weekly survey, we asked participants to list out dashboard signals that they viewed more often than others. We found that participants paid more attention to various signals. R3P1 and R3P9 paid more attention to `Basic Stats` at the top of the dashboard as they provide an overview of the projects' status. R3P2 cared more about the `time to respond to issues and PRs` as he considered "fast response" to issues and PRs much more important than the other three goals. R3P4 and R3P7 mentioned that the trends are useful. The signal that is mentioned the most is `Conversations that Need Your Attention` (R3P4, R3P5, and R3P7) because it is providing maintainers actionable items.

Although in the previous two rounds of interviews, we found that comparison was less useful to participants R1s and R2s, it was considered useful by some diary study participants (R3P2, R3P3, and R3P5). The comparison signals became more useful probably because they were being compared with projects they chose to be peers or competitors (by reporting them in the initial survey). However, R3P11 pointed out that comparison was difficult among projects because some projects have full-time contributors whereas some others do not.

Confusing signals While participants agreed that most of the signals are "*self explanatory*" (R3P2), some of them pointed out that the `Conversation Tone Analysis` part was confusing (R3P1, R3P2 and R3P5). R3P1 reported to us that he "*wanted to learn more about what the numeric score was. First, it would make more sense if it were just a percent (0%-100%), [but] it's currently a unitless number.*" On top of the confusion on the measurement, we suspect the lack of toxic conversations made the `Conversation Tone Analysis` empty and useless. None of our diary study participants had any conversations flagged by the Perspective API.

However, we report the highest toxicity and identity attack scores regardless of the presence of any potentially toxic conversations, *i.e.*, toxicity or identity attack scores > 0.7. Future researchers can explore other ways of reporting toxicity or other tools for detection.

Helpful tips The majority of the participants considered the tips in `Conversations that Need Your Attention` to be useful (R3P2, R3P3, R3P4, R3P5, R3P7, R3P9, and R3P11). Some participants also pointed out some tips that helped them improve specific parts of their projects. R3P7 told us that after viewing our tips on adding a Code of Conduct, he planed to add one soon. Several other participants mentioned tips of `Features that Affect Project Attractiveness` to be useful (R3P1, R3P2, R3P4, R3P5, and R3P11). R3P4 and R3P12 thought the tip in the section `Conversations by Label` was useful. Unfortunately, despite that maintainers considered some of the tips as useful, except for R3P7, who would add a code of conduct, none of them made adjustments yet. It is likely that our diary study was too short for maintainers to take big actions.

In summary, many of our diary study participants found this dashboard useful for themselves or for most maintainers and their level of confidence in supporting community health increased. However, our dashboard has not had any effect on maintainers' actual workflow yet.

5.5 Discussion

Our study takes the first step towards visualizing signals that are related to diversity and inclusion of open source software projects but are hard to observe on current social coding platforms. From the user studies, we received positive feedback on our dashboard's usefulness. In this section, we discuss some implications of our study and ideas for future research.

5.5.1 Implications for Design

Provide actionable feedback

Future work can explore the balance between simply displaying information that reflects the project's status and providing specific tips or instructions for maintainers to follow or implement. During our interviews, some participants appreciated that, in the GitHub issue version, we only provided maintainers with information and did not ask them to perform specific actions. However, some other maintainers reported that many of the tips in the web page version were useful. We argue that displaying only information limits the effectiveness of our dashboard if we do not also provide possible interventions backed by rigorous empirical studies. The amount of tips we should provide can be very nuanced and needs further investigation.

Interactive dashboard

Different participants placed their attention on different signals. For example, some of them considered `Conversation Tone Analysis` to be the best selling point, whereas some others considered `Conversations that Need Your Attention` to be the most useful and actionable items. Since in most cases, participants' projects had few to no toxic conversations during the study period, our current design placed `Conversation Tone Analysis` in a lower position. Such layout might not suit all maintainers' preferences. We also learned from the diary study that people may also care more about other signals, such as `time to respond to issues and PRs`. In the future, designers can make the dashboard more interactive and allow users to freely organize tabs and sections.

Signals to reflect community interactions

Finally, we suggest social coding platforms incorporate some of our signals into their design. When designing the dashboard, we made sure that our features were not redundant with the ones GitHub are providing. For example, GitHub already checks (on each project's `Insights -> Community Standards`) if a project has a README, among other forms of documentation, such as a contributing guidelines and a codes of conduct — all of which have been found to associate with higher project attractiveness to new contributors [88].

Therefore, we argue that our signals are good compliments to the ones displayed on GitHub's Insight page by focusing more on the quality of interactions among contributors and maintainers (coincidentally, GitHub already added statistics on the number of issue and PRs closed each week or month while we were conducting interviews). Our dashboard provides more insights into issue and PR activities, including signals that are found to be associated with contributors' negative feelings, *e.g.*, the number of comments and the time to close a conversation [47, 89].

All our signals can be easily computed using trace data provided by GitHub. Many of the signals we include in our dashboard are requested by maintainers, through our email and think-aloud interviews. Our think-aloud and diary studies validate that these signals can provide extra help for maintainers to better monitor their community.

5.5.2 Implications for Researchers

Although our dashboard was considered useful by many participants, the actual effect on maintainers' management is still limited. Researchers can conduct field studies of longer terms to test out how the dashboard can affect maintainers' strategies and how it will impact an open-source project's inclusion.

The `Conversation Tone Analysis` part needs further exploration. Most of our interview participants and all diary study participants did not have any conversations with toxicity score or identity attack score above our threshold (0.7) during the study period. As a result, the `Conversation Tone Analysis` section was not as useful as it could be and it even confused some participants. Future researchers can explore alternative ways of measuring conversation tone and new mechanisms of flagging potentially inappropriate comments.

Future studies can also explore ways to incorporate more signals. For example, from our interviews, we also collected many signals that maintainers consider important but were hard for us to measure, such as the status of custom continuous integration (CI) builds. There are, however, many standard badges to reflect CI status [27], and these could be further integrated into a dashboard like ours, although we expect that integrating signals such as ours into the platform UI (where CI badges are already available) would be more fruitful, to reduce context switching.

Given the prevalence of bots [318, 319], interactions between human and bots are also important to consider in a maintainer dashboard. Our dashboard did not make specific allowances for the presence of bots within a project or display their activity in a different way from other contributors. A dashboard like climate coach could help maintainers assess where and how to utilize bots to support contributors. It could be useful for project owners to understand how the use of various bots is associated with other participation signals, *e.g.*, contributors could be deterred by interaction with certain bots.

5.6 Limitations

One limitation is the low gender diversity in our participant pool. Although we managed to recruit 4 women maintainers for our diary study, we only had 1 woman maintainer in our Phase 2 interviews, which were essential to our dashboard design, and no non-binary participants.

The biggest limitation was the short duration of our diary study. Ideally we would have like to conduct a longer term diary study to examine whether and how maintainers could integrate our dashboard into their process. In addition a longer study would allow us to examine the impact of dashboard use on project outcomes. Although our results show that many maintainers considered our dashboard to be useful, without a true longitudinal study, we are not able to measure the effect that our dashboard has on the community.

5.7 Conclusion

This paper presents Climate Coach, a dashboard we designed to improve the health of open-source communities. We first identified signals that reflect team inclusion by conducting a literature review and email interviews with maintainers. Based on the signals we identified, we designed a dashboard prototype. We performed two rounds of interviews and think-aloud studies with maintainers to improve our design. We tested the effectiveness of our dashboard with a two-week diary study with maintainers. Our results show that displaying signals that reflect various dimensions of team inclusion can increase maintainers' awareness of their community health and help them improve their confidence of supporting community health.

5.8 Interview Protocol - Climate Coach

Hello, thank you for taking the time to talk with me today!

We are doing a research study on how to design a support tool for helping maintainers monitor the climate of their project.

I and my colleagues are working on this study for <institute name>. If you have any questions about the study afterwards, desire additional information, or wish to withdraw your participation please contact me by email at <researcher email>. If you have questions pertaining to your rights as a research participant; or to report concerns to this study, please contact the Office of Research Integrity and Compliance at <institute name>. Their email is ... and their phone is ...

During the interview session, we are going to ask you some questions about your project maintenance experiences and behaviors and show you some designs to get your feedback. We will ask you to verbalize your thoughts while viewing the designs. The interview should take around 45 minutes - 1 hour.

In order to participate, you must be 18 years of age or older. Your participation is completely voluntary. All responses will be de-identified, and we will keep your answers confidential. There is no compensation for participating.

With your permission, we will also collect public data from your project and data that are brought up during the interview.

Please refrain from discussing sensitive information about yourself or third parties that would put them at risk for civil or criminal liability or damage to their financial standing, employability, or reputation.

Please do not use the real names of other individuals in order to avoid the collection of identifiable and potentially private information about a third party.

Everything will be anonymous and confidential. No one will be identified by name or any other specific characteristics.

There are no “right” or “wrong” answers, and we really appreciate your participation.

We’d like to record the audio of this interview for internal notetaking and analysis purposes. The recordings may be sent to a third-party transcription service to create a written transcript of our conversation for analysis. Only the members of our research team and the transcribers will have access to these recordings and their transcripts. Is that OK with you?

[...Get confirmation...]

We’d also like to record the video of this interview, also for internal notetaking and analysis purposes, meaning only the members of our research team will have access to these recordings. Is that OK with you?

[...Get confirmation...]

You can let us know to stop the recording during the interview if you say anything you would like removed from the record.

We may review publicly available data from GitHub or other online sites regarding your contributions. Is this OK with you?

[...Get confirmation...]

And finally can I verbally confirm that you are 18 years or older, have understood the consent information presented, and wish to continue with the study?

[...Get confirmation...]

5.8.1 Background about the participant

Tell me a bit about who you are and what you do.

5.8.2 Background about the project and their role

What is your role on Project X?

5.8.3 Project community

(if maintainer/owner) Are you the sole maintainer or are there others involved?

Tell us about the community for Project X

Who is a part of the community?

How do you interact with them?

How do people interact with each other?
Can you give an example?

Can you show us a typical example of how you interact with the community? It can be an issue or a PR.

Tell us about the health of the community

How well is the community doing?
How do you know that?

Are there any practices or activities you engage in to encourage community building?
What are they?
How did you decide to do this?

What challenges, if any, is the community facing?

Have you observed any conflict on your project?
Can you give me an example? How often do things like this happen?

How did you resolve that conflict?
Why did you resolve it like that?

Has there been any behavior you would consider toxic (inappropriate) on your project?
What was it? How did you handle it? (Why)

What about other projects?
How did you observe others handling it?

Project management / learning

Do you engage in any activities to manage the community?
What are they?
How / where did you learn those? Give an example
How well are they working?

5.8.4 Think-aloud

<transition - explain think-aloud> Now we're going to show you some designs that include reports about your project and we want to get a sense of how you understand them. There's

no right or wrong answers but we want to observe your thought process as you interact with the (design / report).

We'd like you to think aloud while looking through the designs. What we mean by that is we'd like you to tell us everything you're thinking or wondering while looking at the reports. We won't answer questions during, but you can say them aloud if they cross your mind. The most important part is that you keep talking, so if you are silent for any long period of time, we will ask you to talk. Like if I were going to think aloud while searching for the raise hand feature on Zoom I would say... (talk through example).

[Show example report, ask them to walk us through their thoughts]

[Example report]

5.8.5 Post think-aloud questions

What metrics do you consider important/do you want to know about/are there any we left out?
Community members' wellbeing?
Project's progress/wellbeing?

Are there any projects you think have a healthy community behind them?
What are they?
Why do you think they are healthy? (probe for examples / detail)

Are there any projects where you think the maintainers are doing a particularly good job?

What are they?
How do they relate to yours if at all?

Are there any projects you consider to be peers?
What are they?
Why do you consider them a peer?

Are there any projects you consider similar to yours?
What are they?
Why do you consider them similar?
Do you look at what they are doing? What aspects?

Are there projects you consider competitors?
What are they?
Why do you consider them competitors?
Do you look at what they are doing?
What aspects?

As a maintainer, what format would you want to receive this report in? Email, public issue, etc.

5.8.6 Diversity

Towards the end: how diverse is your project in terms of gender/ethnicity/*etc.*?
Do you engage in any practices or activities to encourage diversity?
What practices do you think would be helpful in improving diversity?

5.9 Diary Study Protocol

5.9.1 Procedure Description

Total time expectation from participants: 3 hours Total cost per participant: $50 Goal number of participants: 8-10 Duration of procedure: 2 weeks

Initial Survey + Onboarding Session (30 minutes) Initial survey - 20 minutes Google form filled out independently by participant Consent information + info about the study structure Background information about the maintainer's identity, habits, and project dynamics At the end of survey, have them sign up for onboarding session time slot Onboarding session - 10 minutes Brief video call (Zoom) Explain logistics of study and weekly survey Show them the dashboard, make sure they understand basic setup Answer any questions the participant has Establish social connection with participant

Weekly usage (30 minutes each week x 2 = 1 hour total) Participants can freely use the Climate Coach dashboard as little or as much as they want during the study. Ask participants via email (sent out each Friday) to complete brief weekly surveys about how they used the dashboard that week. Survey itself should only take 15 minutes; the other 15 minutes account for potential time spent looking at the dashboard Participants should complete the survey within 48 hours of receiving it.

Exit Survey (30 minutes) Survey with questions to get feedback on dashboard and compare responses from initial survey

5.9.2 Initial Survey

(Section 1) Introduction

Hello, thank you for taking the time to participate in our study! We are doing a research study on a support tool designed to help maintainers monitor the climate of their project. This initial survey contains questions about your background information and your involvement in open-source development. It will also explain the logistics of the study.

My colleagues and I are conducting this study as part of the <lab name> and <lab name> research labs in the School of Computer Science at Carnegie Mellon University. If you have any questions about the study afterwards, desire additional information, or wish to withdraw your participation, please contact me by email at [email].

If you have questions pertaining to your rights as a research participant; or to report concerns about this study, please contact the Office of Research Integrity and Compliance at Carnegie Mellon University. Their email is irb-review@andrew.cmu.edu and their phone is 412-268-1901 or 412-268-5460.

(Section 2) Study Logistics Information

This study consists of 3 main parts:

Initial Survey In this survey, we will first ask some brief questions about your background. Then, we will ask you questions about your project maintenance experiences and behaviors. Lastly, we will invite you to sign up for a 10 minute time slot for an Onboarding Session over Zoom where we will explain the dashboard and setup for this study.

Weekly Usage Survey We will email you a survey to fill out once a week for the next 2 weeks. The survey should take about 15 minutes to complete. It will consist of questions pertaining to the dashboard and your project maintenance behavior. You may visit the dashboard as little or as much as you would like throughout the week. Please fill out this survey no later than 48 hours after it is received.

Exit Survey At the end of the 2 weeks, we will send an email with the Exit Survey. This survey will ask about your experience with the dashboard and for any final feedback about the dashboard. We will also ask if you have any other questions or comments about the study. Compensation: Participants will be compensated $50 (USD). If you wish, you may give this compensation to an open source project or foundation of your choice. We will notify you that the compensation has been processed at the end of the study.

5.9.3 Onboarding Interview (Script)

Introduction

Hello, thank you for taking the time to talk with us today! We received your response to the initial survey, and we greatly appreciate your participation in this study.

The purpose of this Zoom meeting is to further explain the study and show you the dashboard that we have generated for your open source project community. This is an opportunity for us to meet you and answer any questions you may have about the dashboard or the logistics of this study.

As a reminder, we are doing a research study on a support tool for helping maintainers monitor the community health of their project.

My colleagues and I are conducting this study for the School of Computer Science at <institute name>. We would also like to remind you of additional resources available to you, which were also presented in the Consent Information section of the initial survey.

If you have any questions about the study afterwards, desire additional information, or wish to withdraw your participation, please contact me by email. If you have questions pertaining to your rights as a research participant; or to report concerns about this study, please contact the Office of Research Integrity and Compliance at Carnegie Mellon University. Interviewer email: Office of Research Integrity and Compliance at <institute name>: (email) (phone)

[share screen to show logistics slides]

Now, we will go over the logistics of the study. This study consists of 3 main parts: This Onboarding Session will take about 10 minutes. We're going to explain the logistics of the study, show you the dashboard and make sure you understand the basic setup, and answer any questions you may have. After this session, you will have two weeks to use the dashboard in your open source project workflow. We will send you a weekly usage survey at the end of each week, which should take around 15 minutes to complete, in addition to any time you spend viewing the dashboard. You may visit the dashboard on your own time as little or as much as you would like throughout the week. Each Friday morning, we will email you a survey to fill out for that week. The survey will consist of questions pertaining to your experience using the dashboard, as well as questions about your project maintenance behavior. Please fill out this survey no later than 48 hours after it is received. Last is the exit survey which should take around 30 minutes. At the end of the 2 weeks, we will send an email with the Exit Survey. This survey will ask you about your experience with the dashboard and for any final feedback about the dashboard.

Do you have any questions so far about the logistics of the study?

[... Answer any questions interviewee might have ...]

Additionally, you will be compensated $50 for your participation. If you wish, you may give this compensation to an open source project or foundation of your choice.

In the initial survey, you confirmed are 18 years or older, and consent to our use of publicly available data from GitHub for use in the dashboard. Can I verbally confirm that you have understood the consent information presented, and wish to continue with the study?

[... Get confirmation ...]

Dashboard Introduction & Questions

I will send a link to the dashboard in the chat now. Please take 5 minutes to view the dashboard and the metrics on it. If any questions occur to you during this time, please feel free to ask me out loud or in the chat.

[After 5 mins has passed]

In those 5 minutes, hopefully you had some time to look over the dashboard and its metrics. Now I am going to ask a few questions to review some sections of the dashboard. I'll put these questions in the Zoom chat for your reference.

1. According to the dashboard, how many new contributors have submitted issues in the past week? [0]

2. According to the dashboard, in the last week, what was the average number of comments on an issue before it was closed? [2]

3. According to the dashboard, what is the most common issue label in your project? [new term requested]

Further questions

Thank you for taking the time to join this call and complete the onboarding session! After this session, I will email you with the information that we covered here, including the study logistics and the link to your dashboard. Do you have any more questions about this study or the dashboard? [pause...] You may also ask questions at any time via email.

5.9.4 Weekly Survey Questions

Introduction

This is the survey for Week (1-2) of the 2-week study conducted by the <lab name> and <lab name> labs at the School of Computer Science at Carnegie Mellon University.

At the beginning of this study, we shared with you the link to a dashboard report for your open source project. As a reminder, you may freely visit this dashboard site as much or as little as you would like for the duration of this study.

The purpose of this survey is to learn more about your activities as an open source project maintainer in the past week. Additionally, we will ask questions about your engagement with the climate report dashboard.

Please complete this survey within 48 hours of receiving it (*i.e.*, by the following Monday). Thank you for your participation!

Section 1: Maintainer Activity

In the following questions, “your project” refers to the open source project analyzed in your dashboard report that we provided at the beginning of this study. Please answer questions with respect to this project only.

WQ1. What types of contributions has your project received in the last week? (select all that apply)

- Bug fixes
- Requests for bug fixes
- New features
- Suggestions for new features
- Documentation updates
- Other

WQ2. Which of the following best describes your level of project maintenance activity in the past week?

- Spent more time than usual on project maintenance tasks
- Spent about the usual amount of time on project maintenance tasks
- Spent less time than usual on project maintenance tasks
- Did not spend any time on project maintenance tasks

WQ3. Approximately how many hours did you spend on maintainer duties for your project in the past week?

WQ4. Approximately how many times this week have you responded to issue comments?

- None
- 1-3 times
- 4-8 times
- 10+ times

WQ5. Approximately how many times this week have you responded to pull request comments?

- None
- 1-3 times
- 4-8 times
- 10+ times

WQ6. How would you describe the tone in discussions related to work on your open-source project?

- Multiple discussions with negative tone
- Some discussions with negative tone
- Mostly neutral tone in discussions
- Some discussions with positive tone
- Multiple discussions with positive tone

WQ7. Select any words that describe the tone in discussions related to work on your open-source project:

- Friendly
- Tense
- Professional
- Informal
- Productive
- Honest

- Hostile
- Complaining
- Supportive
- Polite
- Rude
- Welcoming

Section 2: Dashboard Engagement

WQ8. How often did you check the dashboard this past week?

- Once
- 2-3 times
- 4-5 times
- 6+ times
- I did not check the dashboard

WQ9. Are there specific parts of the dashboard that you viewed more often than others? If so, which sections?

WQ10. Did you click on any of the links to articles or external resources? (do not include links to your own GitHub page)

- Yes, I read a linked article
- Yes, I read resources about the metrics / API documentation
- Yes, I read both an article and resources about the metrics
- No, I did not click links

WQ10-2. If Yes - Why did you decide to click the link and read further?

WQ11. Which informational tips were most useful to you?

- Conversations that Need Your Attention tip
- Conversations by Label tip
- Features that Affect Project Attractiveness - Activity Level
- Features that Affect Project Attractiveness - Scaffolding
- Features that Affect Project Attractiveness - README file
- Features that Affect Project Attractiveness - Inclusive Language

WQ12. Are there any metrics that are confusing in your opinion?

WQ13. How reliable/unreliable did the metrics seem based on your experiences on GitHub this week (1 - 5; 1 - very unreliable - 5- very reliable)?

- Basic Stats
- Issue Author Stats
- Pull Request Author Stats
- New Authors
- Issue Response Time
- Pull Request Response Time
- Long-Standing Open Threads
- Issue Activity
- Pull Request Activity
- Lengthy Open Threads
- Conversation Tone Analysis
- Conversations by Label

- Comparison to Similar Repositories

WQ14. Are there any questions that you have about a specific section of the dashboard or the dashboard overall?

WQ15. Are there any other feedback or comments you have about this dashboard?

5.9.5 Exit Survey Questions

(Page 1)

This is the final survey for the 2-week study conducted by the <lab name> and <lab name> labs at the School of Computer Science at Carnegie Mellon University.

The purpose of this survey is to learn about your habits as an open source project maintainer and your engagement with the climate report dashboard.

The compensation for participation in this study takes the form of a $50 (USD). If you wish, you may give this compensation to an open source project or foundation of your choice. We will process the payment to you shortly after your completion of this survey. Thank you for your participation!

(Page 2) Maintainer Workflow

EQ1. To what extent are you looking for new contributors on your project? (1 - Not interested in gaining new contributors -> 5 -Very interested in gaining new contributors)

(1-strongly disagree to 5-strongly agree):

- EQ2. I feel confident in supporting the community of contributors in my project.
- EQ3. I am unsure about how to encourage a healthy project community.
- EQ4. Increasing the level of demographic diversity among contributors in my project community is important to me.
- EQ5. Increasing the level of diversity in technical expertise among contributors in my project community is important to me.

EQ6. As a maintainer, to what extent do you prioritize the following factors? (On a scale 1-5 low to high priority)

- EQ6-1. Fast response time to issues
- EQ6-2. Fast response time to PRs
- EQ6-3. Creating a welcoming environment
- EQ6-4. Attracting new contributors
- EQ6-5. Attracting a diverse group of contributors

EQ7. How often do you respond to issue comments per week?

- None
- 1-3 times
- 4-9 times
- 10+ times

EQ8. How often do you respond to PR comments per week?

- None
- 1-3 times
- 4-9 times
- 10+ times

EQ9. After viewing the dashboard this week, what goal(s) do you have for your project community? Please list at least one.

(Page 3) Contributor Community Health

EQ10. How would you describe your project's community health?

EQ11. How would you define diversity in open-source software?

EQ12. How would you define inclusion in open-source software?

(Page 4) Usefulness of the Dashboard

EQ13. Please select how much you agree with each of the following statements (1-strongly disagree to 5-strongly agree):

- EQ13-1. This dashboard made me more aware of the diversity and inclusion within my project.
- EQ13-2. This dashboard caused me to be more aware of my own behavior in regards to inclusivity in the community.
- EQ13-3. This dashboard did not have an effect on my actions as a maintainer.
- EQ13-4. This dashboard was useful to me.
- EQ13-5. This dashboard was not useful to me, but might be useful to other maintainers.
- EQ13-6. This dashboard would not be useful to most maintainers.
- EQ13-7. I looked at the dashboard mainly so I could answer the questions for the weekly surveys.

EQ14. Did you add/modify any features to your project based on the content in the dashboard (example: README)?

- Yes
- No
- Other

If yes, which features were added/modified?

EQ15. How likely are you to continue to use this dashboard after the study?

- Unlikely
- Somewhat unlikely
- Neither likely nor unlikely
- Somewhat likely
- Likely

EQ16. As a maintainer, how would you prefer to receive this website report?

- Social media (*i.e.*, Twitter, Reddit, *etc.*)
- Podcast or blog for developers
- Email
- Other

EQ17. Any other feedback regarding the dashboard?

Chapter 6

Conclusion

This chapter concludes this dissertation by summarizing our contributions and revisiting thesis statement:

> *Social science theories driving computational methods on big data explain the mechanisms behind open-source contributors' sustained participation as well as help us design interventions to improve open source community health.*

Then I will discuss some directions for future research.

6.1 Contributions

In this dissertation, I used the problem of low gender diversity as a starting point and conducted a series of empirical studies to get a better understanding of how to improve diversity and inclusion in each phase of an open-source contributor's career path (Figure 6.1). In the end, I built a dashboard based on the findings from my studies to help maintainers better attract and retain contributors. In this section, I will reiterate my findings on how to attract and retain open-source contributors in each phase of their career trajectory.

From a newcomer to a contributor

In this chapter, we used a mixed-methods approach to study how to help new OSS contributors find a suitable project based on signals available on GitHub. The theory we adopted for this study is the signaling theory. We identified a list of signals that GitHub contributors recommend using when assessing projects and estimated logistic regression models to validate each signal's effectiveness in attracting new contributors.

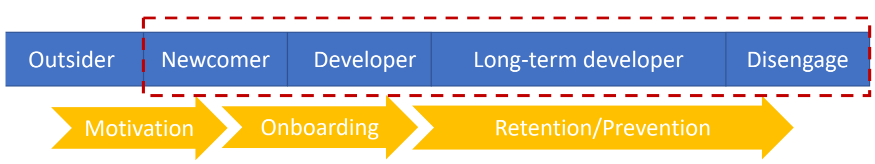


Figure 6.1: An open-source contributor's different phases

The signals we identified can be roughly classified into three categories: popularity, *e.g.*, the number of stars and recent commits; community, *e.g.*, impolite language and responsiveness; and quality, *e.g.*, a well-structured and thorough README and a contributing guideline. However, not all signals are currently easily observable on GitHub. For example, one can quickly evaluate the quality of a README, but cannot easily infer how friendly the community is or how responsive the maintainers are.

This study's results have significant implications for open-source maintainers and the design of social coding environments and intervention tools. We use many of the signals discovered in this study in our climate coach dashboard design.

From a contributor to a long-term contributor

This chapter studied the impact of social capital on sustained participation of open source contributors and, in particular, on gender differences in this impact. We performed a mixed-methods empirical study: we applied survival analysis on a large dataset of OSS contributors and their GitHub collaborators; we also surveyed a subset of these contributors about their perception of social capital to triangulate our findings.

Our results show that being able to obtain more social capital is associated with a higher likelihood of prolonged participation. Bonding social capital, obtained through strong social ties, can provide a sense of belonging and willingness to continue contributing. Bridging social capital, obtained through structure holes, can provide diverse information and more opportunities to continue contributing.

For women, diversity of the project members' expertise becomes more critical to sustain their participation: higher team diversity in terms of prior programming language expertise is associated with decreased risk of disengagement both short- and long-term.

This study reveals valuable signals that are important for improving diversity and inclusion but are currently hard to observe on GitHub, such as recurrent collaboration among teammates and diversity of teammates' technical backgrounds.

Disengagement prevention

This chapter explored how to prevent disengagement by developing automatic tools to detect interpersonal conflict in software development. We cross-pollinated two techniques initially designed for different types of interpersonal conflicts, *i.e.*, pushback and toxicity. Moreover, these two techniques were developed under different contexts, *i.e.*, corporate and OSS, and for different types of discussions, *i.e.*, code review and issues. These two techniques also employed different methods: text-based, *i.e.*, linguistic features, and logs-based, *i.e.*, meta-information. Some of the linguistic features we chose were guided by linguistic theories, such as the politeness theory.

We constructed new datasets and systematically evaluated the two techniques across contexts and types of discussions. We also tested the combination of the two methods in detecting pushback and toxicity. Our evaluation uncovered insights that can be useful for developing detectors for new contexts or types of conversations. More importantly, this study provides strong signals that can help flag potentially problematic interactions for maintainers to review.

Climate Coach

Incorporating findings from all previous chapters, this final chapter presents Climate Coach, a dashboard we designed to improve the health of open-source communities. We first identified signals that reflect team inclusion by conducting a literature review and email interviews with maintainers. Based on the signals we identified, we designed a dashboard prototype. We performed two rounds of interviews and think-aloud studies with maintainers to improve our design. We tested the effectiveness of our dashboard with a two-week diary study with maintainers.

Our results show that displaying signals that reflect various dimensions of team inclusion increased maintainers' awareness of their community health and helped them improve their confidence of supporting community health, which has implications for improving project's diversity and inclusion. However, due to the limited duration of our diary study, we did not observe actual changes in maintainers' management strategies.

6.2 Future work

6.2.1 More forms of diversity

Although this dissertation focuses on gender diversity, and in some quantitative analyses, binary gender diversity, future works can explore other types of diversity. For example, from the demographic perspective, future work can also look into racial, ethnic, and cultural origin diversity. Of course, we will still face challenges in obtaining demographic information from a group of contributors that is large enough for us to perform meaningful analysis.

Other than demographics, future work can also explore diversity in terms of geolocation and tenure. There exist some prior work on geolocation diversity [70], but it is mainly a summary of the number of contributors from different geolocations. Future work can dig deeper into the differences among geolocations, such as culture, education, and attitude towards open-source.

Tenure diversity concerns not only new contributors or experienced, long-term contributors but also how they corporate. Vasilescu *et al.* [58] found that a tenure-diverse team is more productive. More work can be done on how contributors of different levels of expertise can collaborate.

6.2.2 Triangulation

This dissertation employed a mixed-methods approach to discover interventions and measure their effectiveness using the rich signals from social coding platforms (Chapter 2). Some of the findings can be deemed intuitive, such as the number of stars being an indicator of whether a project can attract new contributors. In contrast, some others were unclear until we ran the statistical model, *e.g.*, having a contributing guideline can guide contributors but also create overhead.

Future work should further exploit the mixed-methods approach to triangulate the usefulness of intervention or management strategies. Many qualitative studies reported various problems and proposed several solutions. However, little is yet known about whether the proposed methods can solve the problem and, if so, how effective. Knowledge of the effect size of different interventions can not only help practitioners improve their management strategies but also inform tool design and future study directions.

6.2.3 Intervention deployment

Due to the limited duration of the diary study we conducted in Chapter 5, I was unable to observe significant changes in maintainers' management strategies. As a result, I could not observe the effectiveness of our intervention on a project's level of diversity and inclusion. Since many participants acknowledged the usefulness of many of the signals we included in the climate coach dashboard, I hope social coding platforms can consider incorporating some of them in their UI. In this way, we can test the effectiveness with a larger audience with a longer duration.

6.2.4 Tool design

This dissertation presented two tools for improving diversity and inclusion: an interpersonal conflict detector (Chapter 4) and a dashboard for project climate (Chapter 5). Although the interpersonal conflict detector was not deployed for public usage, its features, such as the number of reviews and tone of the comments, are included in the climate coach dashboard.

Studies have identified plenty of problems, such as barriers that newcomers face. What is lacking is interventions. We must put more effort into developing effective management strategies into practical tools to aid OSS maintainers. We could produce more effective tools with more studies on measuring and validating the effectiveness of management strategies and interventions.

Future studies can further explore how to incorporate more gamification features in tools. Although we added the comparison feature in our climate coach dashboard, it did not turn out to be very effective and served only as a reference for maintainers. Since past studies demonstrated that gamification features have effectiveness in encouraging contribution [320], future studies can explore how to make a better gamification design.

6.2.5 Tools cater to different genders

When conducting the research on signals that contributors should use (Chapter 2), we made use of the GenderMag framework [29], which describes that people of different genders tend to have different ways of interacting with technology. Unfortunately, this dissertation did not discover significant differences in how men and women contributors choose projects and did not explore the gender difference in interpersonal conflicts during code review. Future studies can attempt these problems and devise design guidelines for gender-inclusive tools.

6.2.6 Social network analysis

This dissertation only slightly touched on social network analysis when employing the social capital theory to understand contributors' sustained participation. However, social network theory is a large treasure trunk for research on human aspects in software engineering. For example, prior study [38] found evidence of gender homophily being a disadvantage of women contributors, yet little is known about the mechanism of gender homophily in OSS. Moreover, future studies can explore more on social network positions and evolution, such as network embeddedness [321] and how OSS social networks have changed over time.

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