Recommending Collaborators Based on Co–Changed Files: A Controlled Experiment

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Abstract. *Active collaboration is essential for the success of software projects across the development life-cycle. However, social coding platforms, like GitHub, present challenges in finding potential collaborators with whom they could create new/stronger ties and enhance the quality of contributions. Thus, we conducted a controlled experiment with 35 participants. We asked participants to perform the experiment tasks to find collaborators with similar interests using a prototype recommendation tool and GitHub. We observed that results confirm that recommender based on co–changed files can provide suitable collaborator recommendations to developers of a specific project.*

1. Introduction

Active collaboration is essential for the success of software projects across the development life-cycle. Contributors who appreciate the work or feel responsible for the project are more likely to persist than those driven by particular interests [Shah 2006, Crowston and Fagnot 2018]. Thus, it would be useful to support contributors to stay in the project and make quality contributions [Qiu et al. 2019, Crowston and Fagnot 2018, Barcomb et al. 2019, Barcomb et al. 2020]. However, social coding platforms, like GitHub[1], can present challenges in finding potential collaborators with whom they could create new/stronger ties and enhance the quality of contributions. One of the challenges associated with identifying collaborators is that reliable information is often not readily available [Minto and Murphy 2007, Surian et al. 2011, Canfora et al. 2012].

Previous works have explored developer recommendations for collaborative interactions in software engineering development. For instance, Minto et al. (2007) ranked a list of the likely emergent team members based on a set of files of interest. Surian et al. (2011) recommended a list of top developers that are most compatible based on their programming language skills, past projects, and project categories they have worked before. Canfora et al. (2012) identify and recommend mentors for newcomers in software projects by mining data from mailing lists and versioning systems. Finally, Thongtanunam et al. (2015) recommended pull-request reviewers based on past reviews of files with similar names and paths. Most of these studies mainly focus on specific software tasks and limit the recommended candidates to the core developers of the projects. Inspired by these previous work [Canfora et al. 2012, Thongtanunam et al. 2015], we recommend collaborators based on a set of files that have been mutually edited to increase engagement

[1]https://github.com/

in the project and enhance the opportunities for collaborations, not only core members, code-reviewers, or mentors but also any developer in the project. In this work, we have denominated these mutually edited files as co-changed files [Constantino et al. 2023].

In previous work, we presented a prototype–tool named CoopFinder[2] [Constantino and Figueiredo 2022], which supports two developer recommendation strategies. In another previous work [Constantino et al. 2023], we evaluated these developer recommendation strategies based on co–changed files from the point of view of who receives the recommendations. We observed that these strategies helped developers and maintainers find opportunities for collaborations. To support the strategies, CoopFinder is an interactive visual tool allowing developers to select collaborators and see in which part of the project they have similar interests. The interactive ability of the tool allows developers or maintainers to follow the activities of the collaborator in order to identify potentially interesting collaborators. Based on previous works [Constantino et al. 2020, Constantino et al. 2021], we considered that the set of files of interest represent strong ties in connecting developers of a project. That is, coding tasks may point to opportunities for joint contributions to the project.

Thus, this work describes a controlled experimental study[3] to investigate the developers' perceptions of using CoopFinder prototype. The study involved 35 participants, from which 18 were GitHub users, and 17 were non-users. All participants used both CoopFinder and GitHub to perform a set of seven tasks. To reduce the learning effect on the assessment results, we used the Latin square [Fisher 1992] to distribute the tasks and tools between two groups of (random) participants. Thus, participants answered the background questionnaire, as well as a questionnaire with the experiment tasks for each tools. As results, participants pointed out that CoopFinder is easy to use, intuitive, exciting, and supports project maintainers. Besides, we observed that participants were able to perform tasks more easily using CoopFinder than GitHub. This work makes two primary contributions:

- We propose developer recommendation strategies, supported by a visual and interactive tool to connect collaborators based on a set of files of their interest. Furthermore, the tool provides metadata and links different attributes that could not be analyzed using the GitHub interface.
- We evaluated the usability of CoopFinder with 35 developers. About 51% of them are collaborators and maintainers of real-world open-source projects hosted on GitHub.

Our comprehensive replication package is available online for future replications/extensions[4]. The remainder of this paper is organized as follows. Section 2 presents the problem statement. Section 3 presents an overview of the developer recommendation strategies related to the design, implementation, and how to use the tool. Section 4 describes the study design. Furthermore, we analyze and report the results of this study (Section 5). In Section 6 some threats to the validity are discussed. Finally, we end this paper with some concluding remarks and discuss directions for further work (Section 7).

[2]https://homepages.dcc.ufmg.br/ kattiana/coopfinder/welcome.html

[3]As required, the study was approved by the University's (UFMG) Committee for Ethics in Research - Protocol number: 55476922.0.0000.5149.

[4]https://github.com/kattiana/coopfinder

2. Problem Statement

Previous works show that developers usually ask for help from the core team members, who should be expected to share their motivation, knowledge, and experience [Minto and Murphy 2007, Kononenko et al. 2016]. However, this may not always work as the core team members could be too busy to respond [Yu et al. 2015, Gousios et al. 2015, Steinmacher et al. 2018]. Other experienced developers outside of the core team could also be helpful, and might be more available. That is, all collaboration is essential for the project to succeed [Gamalielsson and Lundell 2014]. Hence, all contributions should be appreciated and encouraged [Pham et al. 2013, Gousios et al. 2014, Pinto et al. 2016].

Previous research also mentions that not having enough people to perform core team roles, such as maintainers, supporters, and reviewers, impacts the sustainability of the project [Jiang et al. 2015, Costa et al. 2021]. Developer turnover can also have a negative impact, as a small group of developers may become overloaded with information and knowledge [Avelino et al. 2016, Ferreira et al. 2017], while others may have limited access to knowledge-sharing opportunities (e.g., collaborations, discussions) [Tamburri et al. 2015]. These situations can lead to frustration and encourage developers to leave the project. These issues all relate to how developers interact with each other and how these relationships affect the project. Therefore, it is crucial to optimize collaboration among project developers and maintain a balanced team.

3. Developer Recommendation Strategies

Developer Recommendation Strategies are supported by COOPFINDER, a prototype tool that enhances opportunities for collaboration in a project based on co-changed files. These co-changed files refer to files that two or more developers have modified. COOPFINDER is an interactive and visually-rich web application that helps connecting developers of these files.

3.1. Developer Recommendation Design

COOPFINDER implements two developer recommendation strategies, namely STRATEGIES 1 and 2, which are based on co–changed files. For STRATEGY 1, the *number of commits* was mined to determine the frequency of file modifications by a developer. For STRATEGY 2, the *number of changed lines of code (LoC)* was extracted. This metric computes the sum of code lines added and removed by a developer in a specific file [Constantino et al. 2023]. Figure 1 presents an overview of the steps required to recommend a developer to another developer in the software project, as follows.

Step 1 – Feature Extraction: The modification history made by all developers in a project was extracted concerning the inputs, as illustrated in Figure 1. The GitHub platform, a social network hosting projects and supporting the fork & pull model, was utilized for this purpose. GitHub developers create copies of the original repository and make changes in their respective copies. Once these changes are finalized, they have the option to submit them back into the original repository via a pull request.

Step 2 – Changed File Scoring: We performed file mining for each developer of the project by extracting the set of co–changed files. This set of files was then ranked using the Term Frequency – Inverse Document Frequency (TF–IDF) algorithm [Salton 1989].

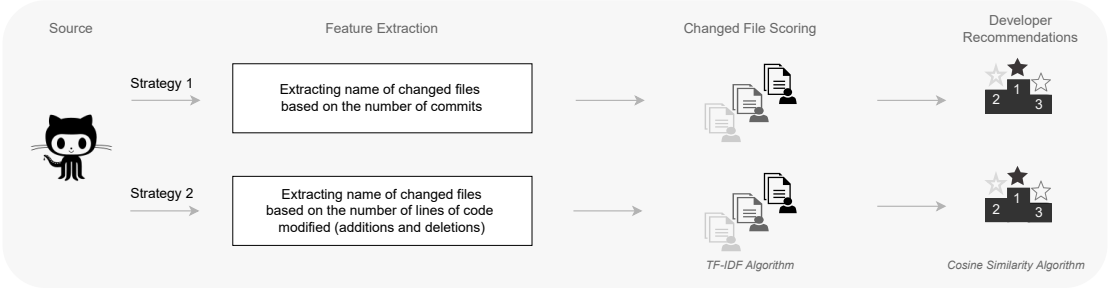

Figure 1. Two developer recommendation strategies [Constantino et al. 2023].

The resulting rank of relevant files for each developer is presented in Figure 1. We repeated this step for both strategies, yielding different ranks for each developer.

Step 3 – Developer Recommender Model: The rank of relevant files for each developer of the project, calculated using the vector space model, was utilized to calculate their similarity via the widely-used cosine metric [Salton 1971, Salton and Harman 2003]. This metric has been extensively employed [Rahman et al. 2016, Franco et al. 2019] due to its ability to quantify the similarity of two objects [Ricci et al. 2011]. We repeated this step for each strategy, as shown in Figure 1.

3.2. Implementation Technologies

Our web tool is based on client-server architecture and utilizes visualization techniques. The server-side is implemented in Python 3[5], with the help of the scikit-learn libraries[6], a free machine learning library for Python. For the views in COOPFINDER, we employed the HighCharts[7] analytical data visualization components, a JavaScript library that enables the manipulation of documents based on data. Finally, we utilized the Bootstrap Framework[8] components, which include various stylesheets and jQuery plugins[9], to create an interactive user interface. Our choice of these technologies was driven by the goal of providing a dynamic exploration and visualization experience.

3.3. Interface and Interaction

The screenshots of COOPFINDER related to the list of contributors of a selected project are depicted in Figure 2. This list includes all contributors who have modified any files in their copies from a selected project from GitHub, as described in Section 3.1. In Figure 2, Frame (A) displays project information, such as the repository name, number of stars, number of forks, and number of open issues, to which the collaborators belong. Frame (B) presents a table of all collaborators of the selected project. For each collaborator, the table provides their developer information, including their avatar, name, fork, number of followers, number of following, number of commits in upstream, number of non-merged commits, and the date of their last commit. Frame (C) displays code activity for upstream and non-merged commits, along with the last commit date. This helps users assess the status of the collaborators in the project, including their activity level based on merged

[5]https://www.python.org/
[6]https://scikit-learn.org/stable/index.html
[7]https://www.highcharts.com/
[8]https://getbootstrap.com/
[9]https://jquery.com

commits and last commit date. Recent non-merged commits may signal a need for assistance. Furthermore, maintainers can review the interests of the collaborators in the project or build teams around of their co-changed files. Finally, the button *"Run"* runs the algorithms of the recommendations and the results are presented as following.

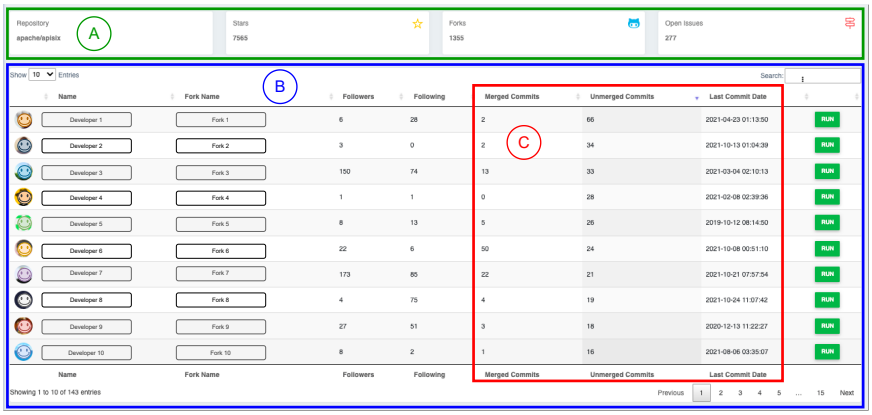

Figure 2. Overview of the contributors information from a specific GitHub project [Constantino and Figueiredo 2022].

Figure 3 depicts a screenshot of COOPFINDER with a list of recommended collaborators for the target developer, which may vary depending on the selected strategy and the rank of relevant files for each project developer, as described in Section 3.1. Frame (D) displays project information, such as the repository name, number of stars, number of forks, and number of open issues, to which the recommended collaborators belong. Frame (E) presents information about the target developer, such as their name, avatar, last commit date, number of total commits, followers, and followings. Finally, Frame (F) shows a list of recommended developers with similar interests based on co-changed files.

In Frame (F), users can select one of the recommended collaborators to compare with the target developer shown in Frame (E). Once selected, Frame (G) displays the two chosen collaborators along with their names and forks, linked with their GitHub profile. Frame (H) enables users to analyze the common files of the two developers. Finally, in Frame (I), the recommended developer's expertise (programming language) related to the focused project is presented. This expertise is calculated as a percentage of the total number of files changed in each programming language.

4. Study Design

This section presents the design of an experiment study to evaluate the developer recommendations based on co–changed files supported by a prototype-tool, namely COOPFINDER. Due to the Covid-19 pandemic, we performed the experiment remotely. However, all instructions necessary were available for the participants. Besides, the first author was available to clarify any doubts. To collect the data, we adopted questionnaires specially designed for this evaluation by using the Google Forms[10] service. Next, we describe our goal, research questions, formulated hypotheses, and the research method.

[10]https://docs.google.com/forms, accessed in April 2022.

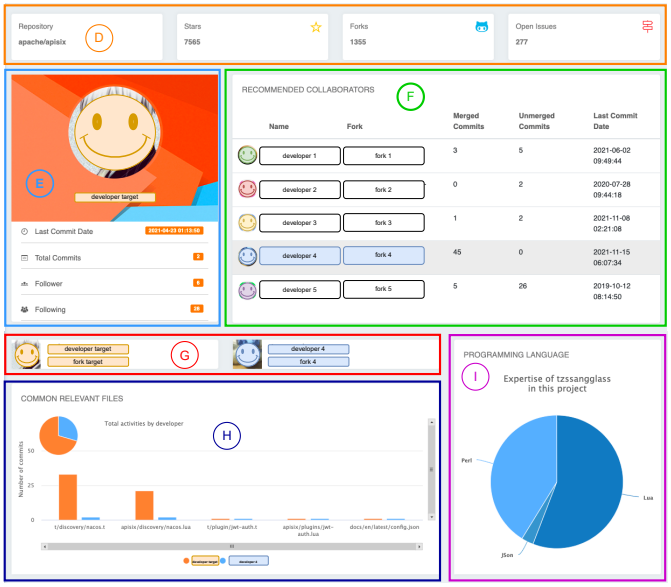

Figure 3. Overview of developer recommendations and their aggregated information [Constantino and Figueiredo 2022].

4.1. Study Goal

We set the goal of our study using the Goal/Question/Metric (GQM) template [Basili and Weiss 1984], as outlined below.

> **Analyze** a tool-supported recommendation strategy
> **for the purpose of** evaluation
> **with respect to** ease of use
> **from the point of view of** developers
> **in the context of** recommendations based on co–changed files in the open-source environment.

4.2. Research Questions

To achieve our goal, we based our evaluation method on the following research questions.

RQ_1 - How easy is it to find collaborators using CoopFinder*?* We compared CoopFinder with GitHub (state-of-the-practice) related to ease of use to find collaborators. Davis (1989) defined ease of use as the degree to which a user believes that using a specific system would be effort free.

RQ_2 - Does the expertise with GitHub impact on the effectiveness of finding collaborators? With this RQ, we relate the background of participants with their experience with GitHub when using the analyzed tools.

4.3. Hypotheses Formulation

We defined hypotheses for RQ_1: in which tool (CoopFinder or GitHub) would it be easier for finding collaborators with similar interests. To answer RQ_1 we evaluated the ease of use of the tools in terms of the scale: 1 (very easy), 2 (easy), 3 (hard), and 4 (very hard). Thus, RQ_1 was turned into the null and alternative hypotheses as follows.

$\mathbf{H}_0$: There is no significant difference related to ease of use between COOPFINDER or GitHub.
$\mathbf{H}_a$: There is significant difference related to ease of use between COOPFINDER or GitHub.

We defined hypotheses for RQ_2: which group (GITHUB USER or NON-USER) would it impact the use of the COOPFINDER or GitHub. To answer RQ_2 we evaluated the answers (correct, incorrect and the blank) that participants should provide for each task proposed. Thus, the null and alternative hypotheses are:

$\mathbf{H}_0$: There is no significant difference in the hit rate between the GitHub users and non-users.
$\mathbf{H}_a$: There is significant difference in the hit rate between the GitHub users and non-users.

4.4. Research Method

To answer the research questions, we planned and performed an experiment study, as shown in Figure 4.

Participant selection. We selected the participants by convenience and using the snowball recruitment technique (i.e., one participant indicates another one, and so on) [Flick 2018]. To be eligible to participate in this study, they must be collaborators of software development projects (developers or maintainers), especially collaborators who work on open-source projects in GitHub. Section 5.1 presents the overview of the participants selected. We received responses from 43 participants. Eight participants did not complete all questionnaires; thus, they were excluded.

Experiment design. First, we asked participants to complete a demographic and background questionnaire (10 minutes). After, we provided a training and explanation session about the experiment related to COOPFINDER and GitHub (10 minutes) (Figure 4). After the training session, we asked participants to perform a set of seven tasks for each tool - COOPFINDER and GitHub (1 hour). We instructed the participants to perform the tasks using both tools. To reduce the learning effect on the assessment results, we used the Latin square [Fisher 1992] to distribute the tasks and tools between two groups of participants, as presented in Figure 4. Each treatment appears only once in each row (group of participants) and only once in each column (tools), allowing a broader evaluation concerning the tool and the group of participants.

Experiment tasks. We defined and adapted the tasks for each tool to have the same goal (Table 1) and difficulty level. Moreover, we presented a brief scenario for each task to direct the activity of the participant to achieve the task goal. For each task, participants should provide an answer for the activity proposed and indicate their perception on how easy it was to perform the task. All scenarios and tasks are available online for future replications/extensions[11].

Data collection. We collected data from the demographic and background questionnaire, the questionnaires of experimental tasks for both tools (COOPFINDER and GitHub)(Figure 4). All data were analyzed, interpreted and reported in the results. All questionnaires, experiment tasks are available online for future replications/extensions.

Quantitative and qualitative analysis. First, we collect quantitative and qualitative data from the online survey and mined data about the participants in social platforms,

[11]https://anonymous.4open.science/r/coopfinder-2B62

Table 1. List of tasks to be performed by participants.

Task ID	Goal
Task 1	Exploring project information
Task 2	Exploring collaborators of a specific project
Task 3	Exploring (non-merged and merged) commits of the collaborators
Task 4	Exploring similar interests among collaborators
Task 5	Exploring contributions to identify relevant files for the collaborators
Task 6	Exploring developer recommendations
Task 7	Exploring expertises of a specific collaborator

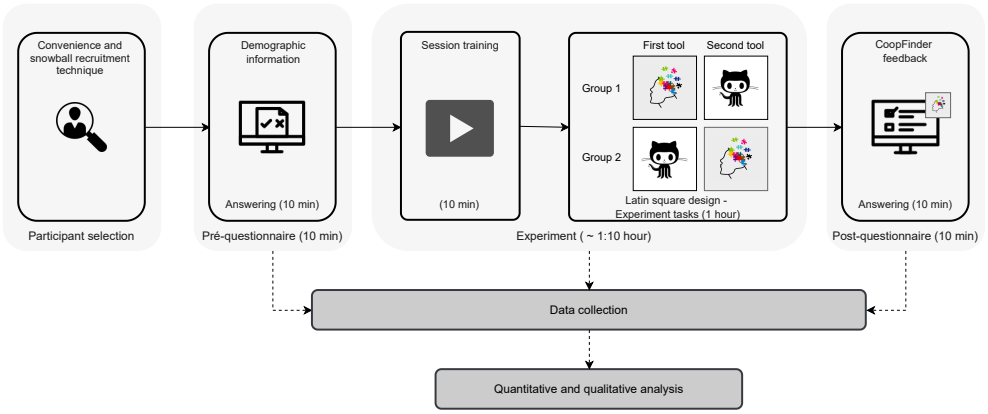

Figure 4. Experiment Design.

such as GitHub and LinkedIn. Section 5 presents the descriptive analysis of these data and Wilcoxon (W) test [Wilcoxon 1992]. We applied the Wilcoxon test for testing the statistical significance. This test is non-parametric; it makes no assumptions about the data distribution. Thus, we can use this test when comparing two groups by continuous or ordinal non-normally distributed dependent variables [Wohlin et al. 2012].

We applied the Chi-Squared test to analyze categorical grouped responses to Likert scale questions and to test the hypotheses of no association between the two groups (i.e., to check independence between two variables). Furthermore, to apply the Chi-Squared test, we should fulfill three prerequisites: (1) random data from a population; (2) the expected value of any cell should not be less than five; (3) if the value in any cell is less than five, it should not occupy more than 20% of cells, i.e., in two by two table, no cell should contain an expected value less than five. Violation of this assumption needs to be corrected by Yate's correction or Fisher's Exact test [Miller and Siegmund 1982].

Ethical considerations. This work involves experiments with human subjects. All participants gave the consent for their answers to be used in this research. Regarding participant data, all sensitive information (i.e., names or GitHub profile) has been previously anonymized to ensure the privacy of participants. Last, this research was approved by the Committee for Ethics in Research of our institution before performing this work.

5. Study Results

This section presents the results regarding each research question of this study. These results provide insights into the participants' perspective.

5.1. Participant Overview

A user study was conducted with 35 participant to evaluate the usefulness and users' satisfaction with the COOPFINDER tool. Table 2 shows some profiling information of the participants related to gender (26 males and 9 females participants), the time of experience in software development contributions. Finally, if they are or not a GitHub contributor.

Table 2. Profiling information of the participants.

		#	%
Gender	Female	9	26
	Male	26	74
Software	None	8	23
Development	Less than 1 year	9	25
Contributing	1 year to 3 years	11	31
	More than 3 years	7	20
GitHub	Yes	18	51
Contributor	No	17	49

About 41% of the participants who are not GitHub contributors declared that they already have tried to make contributions to a GitHub project. We also asked them which kind of actions they have taken on GitHub. Participants P02, P20, and P035 noted that they only opened issues for a project. On the other hand, participant P03 faced some difficulties and declared "*I found exciting projects, but due to entry barriers (understanding of the code, time of dedication) I ended up postponing my work.*" This kind of declaration is in accordance with the literature on barriers faced by developers when trying to collaborate in a project [Steinmacher et al. 2015, Gousios et al. 2016].

Furthermore, participant P21 also declared "*I had difficulty in understanding the code or the lack of help from the leading developers of the project so that I could make the contributions.*" This finding is consistent with literature [Bird 2011, Zhou and Mockus 2011, Gousios et al. 2016] related to the barriers of collaboration, such as lack of knowledge about the code–base and lack of interaction with project members. Besides, this result also reinforces the importance of providing support for developers to find appropriate developers to help them and strengthen the ties among them for improving collaborations in the project.

5.2. How easy is it to find collaborators using COOPFINDER? - RQ_1

In this section, we present the results related to the ease of use of each tool (COOPFINDER and GitHub), i.e., the degree of effort demanded by participants. We applied the same set of tasks with little adaptations for each tool. The tasks are related to exploring information on the project, collaborators, and their contributions and interests. Each task has a specific goal, as detailed in the Table 1. However, the general goal of this set of tasks is to make it easier to find a suitable collaborator with similar interests in co–changed files. Table 3 shows the statistical descriptive (Median (Med), Minimum (Min), Maximum (Max), Distribution (D)), and Wilcoxon (W) test result for each task performed by participants using both tools (COOPFINDER and GitHub). After participants performed each task, they could express their experience related to ease of use with a scale ranging from 1 (very easy), 2 (easy), 3 (hard), and 4 (very hard).

Table 3. Statistic Table.

	CoopFinder				GitHub				W
Tasks	Med	Min	Max	D* 1 2 3 4	Med	Min	Max	D* 1 2 3 4	*p***
Task 1	1	1	1		1	2	2		0.037
Task 2	1	1	2		4	1	4		<0.001
Task 3	1	1	2		4	1	4		<0.001
Task 4	1	1	3		4	1	4		<0.001
Task 5	1	1	4		4	1	4		<0.001
Task 6	1	1	3		4	1	4		<0.001
Task 7	1	1	2		1	1	4		<0.001

*The acronyms used in the columns stand for: Median (Med), Minimum (Min), Maximum (Max), Distribution (D), and Wilcoxon test (W). * Note: The scale ranges from 1 (very easy) to 4 (very hard) on experience of participants for each task. ** p-value < 0.05.*

We applied the Wilcoxon test to compare how easy the tasks were for participants when using CoopFinder and GitHub. According to the Wilcoxon test, the *p-value* for Task 1 is 0.03, and for the others, the *p-value* is less than 0.001, which allows us to conclude that the ease of use is statistically different for CoopFinder and GitHub (Table 3). Indeed, the CoopFinder prototype is a visual and interactive tool for finding suitable collaborators to improve collaborations into projects. Moreover, the tool provides metadata and links to different attributes that could not be analyzed efficiently using the GitHub interface. For example, this information is related to the source code activities of the collaborators of a specific project. Furthermore, this information can help finding collaborators based on similar interests in files that they have modified.

RQ_1 Summary: We observed that participants were able to perform tasks more easily using CoopFinder than GitHub. Wilcoxon test showed that there is statistical difference related to ease of use between CoopFinder or GitHub.

5.3. Does the expertise with GitHub impact on the effectiveness of finding collaborators - RQ_2

In this section, we analyze whether the background related to GitHub expertise of participants can impact the use of the analyzed tools. To this end, we separated the participants into two independent groups (GitHub User group and GitHub non-user group). The former group is for participants who are developers or maintainers of, at least, one open-source project hosted on GitHub. The latter group is for participants who do not have experience with GitHub. Table 4a and 4b present the results about the correct (C), incorrect (I) and the blank (B) answers that participants should provide for the activity proposed. For each independent group, the first and second columns show the number of correct (C) and incorrect (I) answers for each task, respectively. Finally, the *"blank"* (B) column indicates when participants could not answer correctly and left them blank. For this analysis, we applied the Fisher's exact test to compare the hit rate between groups that are GitHub users and non-GitHub users (independent variable) and the answers ("correct", "incorrect", and "blank"), both are qualitative nominal variables.

Table 4a shows the predominance of correct answers when participants performed the tasks using the CoopFinder tool. On the other hand, Table 4b shows the answers

Table 4. Results of tasks performed by GitHub user and non-user.

	User (#)			Non-User (#)			
Tasks	C	I	B	C	I	B	p*
Task 1	16	2	0	15	2	0	1.00
Task 2	18	0	0	17	0	0	**
Task 3	16	2	0	17	0	0	0.48
Task 4	15	3	0	16	1	0	0.60
Task 5	17	1	0	12	3	2	0.15
Task 6	11	7	0	12	5	0	0.72
Task 7	18	0	0	17	0	0	**

(a) CoopFinder

	User (#)			Non-User (#)			
Tasks	C	I	B	C	I	B	p*
Task 1	18	0	0	17	0	0	**
Task 2	7	0	11	9	4	4	0.02
Task 3	2	2	14	2	3	12	0.86
Task 4	2	5	11	2	5	10	1.00
Task 5	3	2	13	4	3	10	0.68
Task 6	2	0	16	3	0	14	0.65
Task 7	15	1	2	14	0	3	1.00

(b) GitHub

*The acronyms used in the columns stand for: correct answers (C), incorrect answers (I), and in blank (B). * Fisher's exact test (p-value < 0.05). ** Test was not applied because the task contains fewer than 2 levels.*

were more distributed when participants used GitHub. The *"blank"* column draws attention to the fact that, except for Task 1, in all other questions, at least half of the participants left the answer blank when they performed the tasks using GitHub. Comments such as *"I didn't find this information"* or *"I don't know"* were common during the execution of the tasks. Participant P22 (GitHub user) explored GitHub to try to answer the tasks correctly. However, P22 stated *"I found it very difficult to find the necessary information on GitHub to do the analyses"*. It reinforces that CoopFinder provides metadata and links to different attributes that could not be explored efficiently using the GitHub interface. Fisher's exact test showed there was no significant difference in the hit rate between the users and non-users groups for almost all tasks (p-*value* > 0.05). When participants used GitHub to perform the task, exploring collaborators of a specific project (Table 3), the Fisher's exact test showed a significant statistical difference for the two samples (p-*value* = 0.02).

RQ_2 Summary: We observed the predominance of correct answers when participants used CoopFinder. On the other hand, we also observed the predominance of blank answers when using GitHub indicating that participants either did not know or did not find the correct answers. In general, Fisher's exact test showed no significant difference in the hit rate between the users and non-users groups for all tasks.

6. Threats to Validity

Even with careful planning, this research can be affected by different factors which might threaten our findings. We discuss these factors and decisions to mitigate their impact on our study divided into categories of threats to validity proposed by Wohlin et al. (2021).

Construct Validity. This validity is related to whether measurements in the study reflect real-world situations [Wohlin et al. 2012]. This kind of threat can occur in formulating the questionnaire in our experiment. To minimize this threat, we cross-discuss all the experimental procedures. Basili et al. (1999) and Kitchenham et al. (2002) argue that qualitative studies play an essential role in experimentation in software engineering.

Internal Validity. The validity is related to uncontrolled aspects that may affect the strategy results [Wohlin et al. 2012]. Since we employed a snowballing approach to sampling our participants, we acknowledge that sampling bias affects the selection of

the participants, namely self-selection and social desirability biases. However, we counteracted this effect by inviting people with different profiles, from various projects, and with diverse backgrounds, seeking out different perspectives. Another threat is the use of statistical tools. We paid particular attention to the suitable use of statistical tests (i.e., Wilcoxon test) when reporting our results. This decreases the possibility that our findings are due to random events.

EXTERNAL VALIDITY. The external validity concerns the ability to generalize the results to other environments [Wohlin et al. 2012]. There are three major threats to the external validity of our study, such as baseline tool, the selected project and participants. First, we chose GitHub as baseline of the experiment, and we cannot guarantee that our observations can be generalized to other tools. Second, we analyzed public and different open-source projects hosted on GitHub, different community sizes, and programming languages, among many available ones. Moreover, we cannot guarantee that our observations can be generalized to other projects. Finally, participants may not reflect the state of the practice developers. Furthermore, our results could also be different if we had analyzed another software development network or projects hosted on other repositories, such as private or industrial projects.

CONCLUSION VALIDITY. The conclusion validity concerns issues that affect the ability to draw the correct conclusions from the study [Wohlin et al. 2012]. The approach used to analyze our experiment results represents the main threat to the conclusions we can draw from our study. Thus, we discussed our results by presenting descriptive statistics and statistical hypothesis tests. Besides, all researchers participated in the data analysis process and discussions on the main findings to mitigate the bias of relying on the interpretations of a single person. Nonetheless, there may be several other important issues in the collected data, not yet discovered or reported by us.

7. Conclusion and Future Work

This work described a controlled experimental study to investigate the perceptions of the developers using COOPFINDER a prototype tool to support two strategies for recommending collaborations. This developer recommendation strategies aim to connect developers of a specific project based on their similar interests. The study involved 35 participants, 18 of which were GitHub users, and 17 were non-users. Participants answered the background questionnaire, the questionnaires for the experiment tasks for both tools.As results, participants pointed out that COOPFINDER is easy to use, intuitive, exciting, and supports project maintainer. Besides, we observed that participants were able to perform tasks more easily using COOPFINDER than GitHub. As future work, we intend to evaluate further combinations of these strategies exploring the source code (libraries, APIs, features) or programming languages as features to improve the developer recommendations. We also intend to evaluate COOPFINDER in real context of use, to see how often the recommendations actually foster collaboration.

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