Exploring the Notion of Risk in Code Reviewer Recommendation

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Abstract—Reviewing code changes allows stakeholders to improve the premise, content, and structure of changes prior to or after integration. However, assigning reviewing tasks to team members is challenging, particularly in large projects. Code reviewer recommendation has been derived based on historical data, where better solutions are those that recommend exactly which reviewers actually performed tasks in the past. More recent work expands the goals of recommenders to include mitigating turnover-based knowledge loss and avoiding overburdening the core development team. In this paper, we set out to explore how reviewer recommendation can incorporate the risk of defect proneness. To this end, we propose the Changeset Safety Ratio (CSR) – an evaluation measurement designed to capture the risk of defect proneness. Through an empirical study of three open source projects, we observe that: (1) existing approaches tend to improve one or two quantities of interest, such as core developers workload while degrading others (especially the CSR); (2) Risk Aware Recommender (RAR) – our proposed enhancement to multi-objective reviewer recommendation – achieves a 12.48% increase in expertise of review assignees and a 80% increase in CSR with respect to historical assignees, all while reducing the files at risk of knowledge loss by 19.39% and imposing a negligible 0.93% increase in workload for the core team; and (3) our dynamic method outperforms static and normalization-based tuning methods in adapting RAR to suit risk-averse and balanced risk usage scenarios to a significant degree (Conover’s test, $\alpha < 0.05$; small to large Kendall’s $W$).

Index Terms—Code Review Recommendation, Mining Software Repositories, Software Quality

I. INTRODUCTION

Code review is the process by which developers assess each other’s code changes [1]. This process can help to prevent bugs in their early stages before they are merged into the code base [2]. The tool-based code review process is known to provide stakeholders with technical [3,4] and non-technical [5] benefits. A popular form of code review, which often involves a tool-based procedure, is called modern code review [7].

Finding reviewers with the time to review a code change and familiarity with the modified subsystems has been a challenge in organizations who adopt code review [8,9]. This is especially the case for large organizations with hundreds of developers. In such organizations, the author of a contribution may not yet have a professional relationship with the team responsible for overseeing the development of all of the components that they have changed. Code Reviewer Recommendation (CRR) aims to help stakeholders to find suitable reviewers [10].

While early reviewer recommendation studies were evaluated against historical records, i.e., who performed each task in the past [11], more recent work explores how recommendation approaches can be used to balance quantities of interest [12,13]. These approaches consider previous interactions of the candidates with the modified files, the workload of the candidates at the time of the code review, and previous interactions between the developers in the project. Candidate reviewers are then ranked based on these metrics, and top-ranked candidates are suggested to decision-makers.

The results from previous studies suggest reviewers who share properties with those who performed similar reviews in the past and improve evaluation metrics such as files at risk. While the measures that have been proposed by previous studies align with important dimensions, the risk of defect proneness has not been explored. The risk of defect proneness of a code change indicates how probable it is for the change to induce fixes in the future. As an intervention, changes with a high risk of inducing future fixes may be assigned to subject matter experts for review. Prior work suggests that subject matter experts may be more adept at identifying problems during the review process [14,15]. However, this intervention is likely to impose a greater burden on key team members.

In this paper, we take the position that an ideal recommendation approach should balance the trade-off between the burden on expert reviewers and the risk of defect proneness. Therefore, we set out to incorporate defect proneness in the reviewer recommendation process. More specifically, we set out to address the following research questions:

**RQ1 How do existing code reviewer recommenders perform with respect to the risk of inducing future fixes?**

**Motivation:** Every code change induces some degree of risk. The degree of risk varies based on the change and its domain [16]. A key goal of the code review process is assessing and mitigating the risk of introducing defects during or shortly after the code integration process [17]. It is crucial to involve subject matter experts in the review process to achieve that goal. Otherwise, if non-experts review high-risk tasks, defects may slip through the integration process. Thus, we first set out to understand how well existing reviewing assignments and CRR-based reassignments perform in terms of risk mitigation.

**Results:** We observe an inherent trade-off between our studied quantities of interest. For instance, the RetentionRec recommender – a reviewer recommendation
approach proposed to minimize the risk of developer turnover-based knowledge loss while ignoring other quantities of interest – reduces files at risk by up to 23.89% with respect to the reviewers who have already performed the review. On the other hand, RetentionRec underperforms in terms of the Changeset Safety Ratio (CSR) – a measure that we propose to indicate the performance of a recommendation approach concerning the safety of the code change process – by 4.56% to 37.07%.

**RQ2 How can the risk of fix-inducing code changes be effectively balanced with other quantities of interest?**

Motivation: Optimizing for other quantities of interests, such as files at risk of turnover, without considering defect proneness is unlikely to perform well due to the inherent trade-offs discovered in RQ1. Therefore, an approach is needed to incorporate defect proneness in recommendation decisions without overly disrupting other quantities of interest. To that end, we propose RAR – a reviewer recommendation approach that aims to incorporate defect risk into recommendations – and set out to evaluate how well it performs.

Results: Our experiments indicate that RAR increases the expertise of reviewers assigned to reviews by 12.48% and the CSR by 80.00% while reducing files at risk of turnover by -19.39% and only increasing the core development team workload by 0.93%. Moreover, we find that project or team-specific tolerance of risk can be incorporated by adjusting the threshold \( P_D \), which is the threshold of the likelihood of fix-inducing PRs at which changes are deemed risky enough to require intervention. The effective \( P_D \) interval is defined as the change interval for which the performance of the RAR is impacted. For instance, in Roslyn, the effective interval of \( P_D \) is 0 - 1; however, the effective interval of \( P_D \) is 0 - 0.3 and 0 - 0.1 for the Kubernetes and Rust projects, respectively. Thus, \( P_D \) must be calibrated to its effective range for RAR to achieve optimal results.

**RQ3 How can we identify an effective fix-inducing likelihood threshold (\( P_D \)) interval for a given project?**

Motivation: The performance of RAR depends on the \( P_D \) setting. \( P_D \) itself is dependent on a project’s past defect proneness. Moreover, different projects may assign different weights to the importance of defect proneness. Therefore, we set out to propose approaches to support stakeholders in tuning \( P_D \) to an appropriate value for their development context.

Results: We propose static, normalization, and dynamic approaches to tune the value of \( P_D \). Results that explore \( P_D \) settings in risk-averse, risk-tolerant, and balanced contexts indicate that the proposed methods affect the performance of RAR significantly. Moreover, the dynamic method outperforms the others in risk-averse and balanced contexts to a statistically significant (Conover’s Test, \( \alpha < 0.05 \)) and practically significant degree (Kendall’s \( W = 0.0727 - 0.543 \), small - large).

### II. Related Work

In this section, we describe related studies on defect proneness prediction and reviewer recommendation approaches.

**Reviewer Recommendation.** The main task of a reviewer recommender is to suggest suitable reviewers for reviewing tasks. Reviewer recommenders often leverage historical data to make recommendations [18] [19]. Other approaches aim to optimize other characteristics, such as workload balance [12] [20] or distributing knowledge [13]. Regardless of the optimization method, when a new Pull Request (PR) is created, the recommender ranks potential candidates based on the score that has been calculated by its objective function.

Recently, however, early work has explored a change in perspective of the goal of the reviewer recommendation process. Kovalenko et al. [21] observed that developers are often aware of the top recommendations of CRR approaches, suggesting that other goals, such as workload balancing, might be more appropriate. Gauthier et al. [22] found that history-based evaluations of reviewer recommenders are often more pessimistic than optimistic since the proposed reviewers who did not perform a review (i.e., incorrect recommendations) often reported high comfort levels with those review tasks. Mirsaeedi and Rigby [13] proposed Sofia, a multi-objective recommendation system that tries to maximize reviewer expertise and minimize the risk of turnover-based knowledge loss, as well as the workload on the core development team. In this paper, we set out to complement the prior work by also incorporating estimates of the risk of inducing future fixes in the recommendation process. To this end, we evaluate three different projects using seven different approaches. We use cHRev [19] as a conventional recommender to suggest reviewers. In addition, we consider greedy recommendation strategies like LearnRec [13], which tries to maximize the learning from a PR. We also evaluated Sofia [13] as a state-of-the-art recommender.

**Defect Prediction.** Defect prediction models are used to help the stakeholders of a project focus their limited resources on bug-prone modules [23]. Practitioners have used defect prediction systems to find bugs in their early stages, reducing technical debt [24] and the effort required to fix them. These models can also help teams identify buggy changes before they are merged into the repository. These defect prediction models are often trained using historical data and then used to assess new code changes by estimating the likelihood that a given code change will induce a future fix (i.e., estimating the fix-inducing likelihood). There have been a plethora of contributions on defect prediction, but we focus below on two lines of work that are most relevant, i.e., (1) approaches to more accurately identify fix-inducing changes and (2) proposed indicators of fix-inducing commits. Just-In-Time (JIT) defect prediction models — like any prediction model — will only be as good as their training data. Since the true set of fix-inducing changes is not clearly labelled in historical software data, heuristic approaches are used to recover that signal.

The SZZ algorithm [25] first identifies bug-fixing commits by mining for keywords such as “fix” or “bug” in commit
messages. Next, potential fix-inducing commits are associated with these fixes by tracing lines that were removed or modified back to the commit(s) that introduced them. Finally, filters are applied to remove potential fix-inducing changes that are unlikely to have caused the bug (e.g., potentially fix-inducing commits that were recorded after the bug was created in the issue tracker). The SZZ algorithm has seen several revisions in the literature [26, 27]. Since improving SZZ is beyond the scope of this paper, we use the off-the-shelf implementation of SZZ available in the Commit Guru tool [28].

The set of indicators that are used to predict fix-inducing changes are derived from the change itself, historical tendencies of the modified areas of code, and characterization of the personnel involved with the change [23]. For example, Kamei et al. [29] used measures of the size, purpose, and diffusion of a change, as well as the historical tendencies of the modified modules and the experience of change authors to estimate the likelihood of a change to induce future fixes. Hoang et al. [30] and McIntosh et al. [31] expanded the set of measures to include review metrics such as iterations, number of reviewers, and comments. Pascarella et al. [32] added more detailed measures such as owner’s contribution lines, and change code scattering. In this paper, we use the set of measures that have been provided by Commit Guru to calculate the 13 metrics similar to Kamei et al.’s set of measures for various Pull Requests (PR) based on PR’s Commits.

Different variables are used as defect prediction model input, usually based on the change, source code metrics and historical data [23]. However, some studies have used code change chunks as well as metrics such as developer networks to determine the buggy commits [33]. In this study, we use the output of Commit Guru to identify commit features. The tool needs a GitHub repository address to perform the SZZ analysis on the repository. Given a specific Git branch, Commit Guru starts analyzing the desired Git branch and identifies the fix-inducing commits using the SZZ algorithm. The implementation details of the Commit Guru tool can be found in a study by Kamei et al. [29]. Commit Guru extracts thirteen metrics for each commit (Table 2 in supporting materials [34]) and a flag that indicates whether the commit is suspected to be fix-inducing. We use these metrics and the fix-inducing flag to predict the defect proneness of code changes.

III. STUDIED DATASETS

In this section, we present the sources of data and the projects used to conduct our study and the rationale for their selection. Data Source. To evaluate RAR, we seek to ground our analysis in a comparison to previous multi-objective reviewer recommenders [13]. Therefore, to obtain a fair comparison, we begin with the same subject systems that Mirsaeddi and Rigby studied [13]. However, two of these projects, CoreFx and CoreCLR have been since merged with the .Net Runtime project. Due to this migration, Commit Guru was unable to obtain the necessary information for the prediction model and rendered us unable to process the master branch for possible fix-inducing commits. As a result, we omit CoreFx and CoreCLR, focusing our analysis on Rust, Kubernetes, and Roslyn. Rust and Kubernetes are community-driven projects, and Roslyn is an industry project developed openly on GitHub. These projects are well-established (more than four years old) with more than 10K PRs. Kubernetes has had a significant impact on cloud computing platforms with more than 3.1K contributors. Roslyn, with 524 contributors, is an open source .NET compiler platform for languages such as C# and VB. Finally, Rust, with 3.8K contributors, is a multi-paradigm, general-purpose programming language. Further details of these projects are listed in Table 1 of our supporting materials [34].

Data Collection. We begin our data collection process by downloading the relevant details from the replication package provided by Mirsaeddi and Rigby [35]. The shared data includes commits, files that have been modified in each commit, developers involved in a PR, a list of developers and reviewers of each PR, and developers’ interaction with the PR. To perform defect analysis, our approach requires a list of the commits that comprise each of the PRs. Moreover, we need to compute the measures listed in Table 2 in supporting materials [34] to train our defect prediction model. We use the GitHub API to gather the additional data for each PR in the data set. We did not use the commits of a PR to calculate additions and deletions since they might have cancelled each other out (e.g., one line added in one commit could be removed in the next commit of the same PR). Instead, we calculate the net number of additions and deletions extracted directly for each of the PRs.

IV. STUDY DESIGN

This study is comprised of two parts: (1) identifying fix-inducing PRs and (2) evaluating reviewer recommendation approaches. This section describes each part of our study and explains the rationale behind our design decisions.

A. Identifying and Predicting Fix-Inducing PRs

Because our approach aims to incorporate the notion of risk in the recommendation process, identifying fix-inducing PRs with which to evaluate our approach is an important part of the study. In this study, we operationalize risk by mining the repositories of the studied projects for defect-fixing, and fix-inducing commits using Commit Guru [28]. Figure [1] provides an overview of our discovery process for risky PRs.

Step1: Extract defect prediction data: We first apply Commit Guru [28] to the studied repositories in order to produce data sets of fix-inducing commits, as well as a popular set of measures for their prediction. Commit Guru clones each repository, computes commit-level measures that share a relationship with risk (e.g. patch size, diffusion), and applies the SZZ algorithm [25] to identify which historical commits have induced future fixes. Finally, a logistic regression model is fit to estimate the riskiness of code changes. Table 2 in supporting materials [34] shows the set of used risk measures.

Although studies by Quach et al. showed some of the limitations of SZZ ([36, 37]), its output is still an indicator of bug-inducing probability. Moreover, we decided not to use
manually verified bug datasets such as the one by Rodriguez-Perez et al. [38] as we wanted to view the effects of the recommendation approaches in their natural habitat, which would normally be automated and include tools such as SZZ.

**Step 1: Identify the buggy commits and their metrics**. The model then estimates the likelihood that each code change will be fix-inducing in the following quarters.

3) **Aggregated risk estimates to the level of PRs**. Using the trained models, we estimate the riskiness of each PR by aggregating the risk measures across all of the PR changes. We use the PR’s commits risk measures to calculate the risk measures for a PR. Table 2 in the supporting online materials [34] has a brief explanation of how each of these risk measures is calculated from the set of commits belonging to a PR. Using the PR risk measures, the model estimates the PR’s likelihood of inducing a future fix. We use the balanced accuracy performance measure to evaluate the performance of our models since our datasets are inherently imbalanced, i.e. there are more non-fix-inducing PRs than fix-inducing PRs. The median balanced accuracy over different periods for Roslyn, Rust, and Kubernetes projects are 75.9%, 50%, and 97.5%, respectively.

### B. Ranking potential reviewers of a PR

As the next step, we use the fix-inducing likelihood of the PR and its risk measures to suggest reviewers for each PR. We evaluate seven baseline approaches (RQ1) as well as our proposed method, RAR (RQ2). We describe the baseline approaches below, and describe RAR in Section VI.

1) **AuthorshipRec**: Suggested by Mockus and Herbsleb [41], the authorship of a file is an important factor when assigning software experts to (reviewing) tasks. Bird et al. [42] formulated the AuthorshipRec in their paper based on the proportion of the files that a developer modified prior to the PR.

2) **RevOwnRec**: Thongtanunam et al. [4] suggested a new reviewer recommender based on the developers’ previous review history. The rationale was that the project code reviewers for each project subsystem are constant most of the time. Similarly to AuthorshipRec, RevOwnRec considers the proportion of a developer’s reviews or modifications relative to all of the reviews and modifications in a PR.

3) **cHRev Recommender**: The cHRev recommender [19] is a popular conventional reviewer recommender. When ranking developers as potential candidates of a code change, cHRev considers the developer’s expertise from previous reviews as well as the recency of the contributions. To rate the fit of a developer D for reviewing a file F, the xFactor was used:

\[
x_{Factor}(D, F) = \frac{C_f}{C_f} + \frac{W_f}{W_f} + \frac{1}{|T_f - T_f| + 1}
\]  

(1)

Where \( C_f \), \( W_f \), and \( T_f \) represent the number of review comments, the number of workdays that D commented on the file’s reviews, and the most recent day that D worked on F, respectively. The prime versions of the variables in the denominator represent the total number used to normalize the output. Then, the fit for each developer is estimated using the summation of the xFactor for all the files in the code change.

4) **LearnRec**: The LearnRec recommender is designed to distribute knowledge among team members. LearnRec suggests developers who are poised to learn the most from reviewing a PR. **ReviewerKnows** has been suggested as a way to measure how knowledgeable a potential reviewer is about a review request [13]. The **ReviewerKnows** estimates how familiar a
We consider \( d = 2 \) in this equation, similar to the original work (e.g., one year) for which the contributor is responsible.

RetentionRec and consistency ratio

The contribution ratio

This metric can be used to create a reviewer recommender that distributes the knowledge among the project developers by assigning the review to the developer with the largest LearnRec.

5) RetentionRec: Although LearnRec seems like a reasonable choice to prevent knowledge loss, in reality, many developers do not contribute to a project over a long time \([43]\). Those who stand to learn the most may leave the project before that knowledge can be put to use. To mitigate this issue, contribution ratio and consistency ratio have been proposed.

The contribution ratio for a developer is the proportion of contributions during the previous particular period of time (e.g., one year) for which the contributor is responsible. The consistency ratio is the proportion of sub-periods (e.g., months) that the developer was actively contributing to the project throughout a study period (e.g., year). As developers become more consistent or more (proportionally) active, the RetentionRec increases, suggesting that it is less likely that they will leave the project.

6) TurnoverRec: Mirsaeedi and Rigby \([13]\) multiplied RetentionRec and LearnRec and created TurnoverRec. This recommender helps with distributing knowledge among the more active members of the development team. Recommending reviewers based on this measure minimizes the risk of turnover-induced knowledge loss caused by developers leaving the company by distributing knowledge among active members.

7) Sofia: Sofia \([13]\) is a combination of TurnoverRec and cHRev whose objective is to distribute knowledge among the more active team members whenever files with a large risk of knowledge loss are present in a PR. The scoring function used for the developer \((D)\) and the code change \((R)\) is:

\[
\text{cHRev}(D, R), \quad \text{if } |\text{knowledgeable}(f)| \leq d, \text{any } f \in R \\
\text{TurnoverRec}(D, R), \quad \text{otherwise}
\]

We consider \( d = 2 \) in this equation, similar to the original work by Mirsaeedi and Rigby \([13]\), to prevent any knowledge loss by leaving one developer from the team.

C. Recommendation Component

We apply these reviewer recommender to our datasets and calculate the recommenders’ scores for all the candidate reviewers. We then rank potential candidates based on the scores. Configurable parameters include the number of reviewers per PR and the maximum number of files per PR for the reviewer’s knowledge. For the purposes of this paper, we choose only the top suggested candidate per PR and randomly replace it with one of the actual reviewers (to match prior work \([13]\)). We only consider PRs with less than 100 files and do not associate the PR with developers’ knowledge otherwise regarding maximum files per PR. It is because one developer cannot perceive large code changes as argued by Bird et al. \([44]\).

V. Evaluation Setup

In this section, we describe the evaluation metrics used to assess the performance of reviewer recommenders and our rationale for selecting those metrics. As explained in Section \([1]\) conventional recommendation approaches aim to recommend the reviewers who performed the task \([19, 45, 47]\). However, Kovalenko et al. \([21]\), suggest that recommending the reviewer who reviewed a PR provides little value to the project. Furthermore, there exist many qualified developers who may not have reviewed PR but would have been comfortable doing so \([22]\). Conventional evaluation methods consider these recommendations incorrect and penalize the recommenders for making such suggestions.

To assess the effect of a recommendation approach on the mitigation of the risk of fix-inducing PRs, we leverage the simulation approach presented by Mirsaeedi and Rigby \([13]\). These metrics quantify previously discussed aspects of the reviewer recommendation process and estimate the performance of a reviewer recommender through history-based simulation. We run simulations for the selected projects and compare the outcome of the recommenders with one another with respect to the evaluation measures. We expand the set of evaluation measures proposed by Mirsaeedi and Rigby \([13]\) to incorporate the CSR — a cumulative measure of the risk of fix-inducing changes in a given period of time. These measures originated from the challenges and expectations of the researchers who studied the code review process and recommendation approaches prior to this study \([1]\).

In the remainder of this section, we explain each of the recommendation evaluation measures we employ in this study. Expertise. Expertise of the reviewers assesses the recommended reviewers by the expertise that they have in the PRs they have been tasked to review. It is the primary evaluation criterion used in past studies \([48, 49]\). Past work has indicated the important role that involving subject matter experts has on the review process \([6, 14]\). To quantify this measure, Mirsaeedi and Rigby \([13]\) proposed the following measure:

\[
\text{Expertise}(Q) = \sum_{R} \frac{\text{FileReviewersKnow}(R)}{\text{FileUnderReview}(R)}
\]

Where \( Q \) is the quarter in which this metric is calculated. A developer is assumed to know a file if they have modified or reviewed the file prior to the PR reviewing task.

CoreWorkload. Having all PRs reviewed by experts is ideal, but there is an inherent trade-off between the time that experts invest in reviewing PRs and the amount of time they have for other development tasks \([14]\). The problem amplifies as projects grow if the core developer teams do not grow as well. Mirsaeedi and Rigby \([13]\) proposed a static core team size of the top 10 reviewers and using the following equation, estimate the reviewing workload that the core team is coping with:

\[
\text{CoreWorkload}(Q) = \sum_{D} \text{NumReviews}(D)
\]
Files at Risk of turnover (FaR). The loss of knowledge caused by knowledgeable developers leaving a project may consume resources and even stall its progress. The File at Risk of turnover (FaR) measures the number of files known by zero or one developer in a period of one quarter. The formula to calculate this measure is:

\[ \text{FaR}(Q) = \{ f \mid f \in \text{Files}, |\text{ActiveDevs}(Q, F)| \leq 1 \} \]

(5)

Where \( \text{ActiveDevs} \) represent the developers who are familiar with the set of files \( F \) and are still actively contributing to the project by the end of quarter \( Q \).

Changeset Safety Ratio (CSR). The replacement of reviewers does not affect the incidences of bugs in our simulation. Instead, to assess the impact of replacing reviewers on risk, we assume that having an expert, preferably one who has recently interacted with files in the code change, will reduce the likelihood of merging fix-inducing code changes [42]. To this end, we formulate the Changeset Safety Ratio (CSR) as a measure of how well the review assignments have mitigated the fix-inducing likelihood of a set of PRs:

\[ \text{CSR}(Q) = \sum_{R} (1 - \text{DefectProb}(R)) \times \text{MaxxFactor}(R) \]

(6)

The DefectProb is the risk estimate of a PR being fix-inducing, and the MaxxFactor is the maximum score of the xFactor (equation 1) among all the suggested reviewers of a PR. The xFactor incorporates both the recency and quantity of fixes that a PR presents is small, we may assign developers with less expertise to that code change without impacting the CSR disproportionately. Increases in CSR indicate that the code change is less likely to be fix-inducing or that the developer’s maximum expertise has increased. In either case, increases to CSR suggest that the review process is performing well in terms of risk mitigation.

VI. EXPERIMENTAL RESULTS

In this section, we describe our experiments, the results and the analysis of the results. We use the percentage of change to evaluate different reviewer recommenders’ performance:

\[ \Delta \text{MeasureChange}(Q) = (\frac{\text{SimulatedMeasure}(Q)}{\text{ActualMeasure}(Q)} - 1) \times 100 \]

(7)

The ActualMeasure and SimulatedMeasure refer to the calculated evaluation metric for the historical data and a simulation run, respectively.

RQ1: How do existing code reviewer recommenders perform with respect to the risk of inducing future fixes?

In this experiment, we seek to determine whether reviewer recommenders mitigate the risk of inducing future fixes by introducing an evaluation measure (CSR).

Approach. For each studied system, we analyze the historical data and fit one model per quarter to estimate the likelihood that a PR is fix-inducing. Then, starting from the second quarter, we use a model fit of the previous quarter to estimate the fix-inducing likelihood of each PR. We use PR metrics listed in table 2 in the supporting online materials [34] as the model’s input. We then rank potential reviewers for each PR using the seven baseline recommendation approaches. For every PR in each studied system, we swap one of the actual reviewers with each of the seven baseline recommendation approaches. For every PR in each studied system, we swap one of the actual reviewers with each of the seven baseline recommendation approaches. Thus, increases to CSR are not unexpected, since coders owners are among the most knowledgeable contributors to whom reviewing tasks may be assigned. However, this assignment prevents others from learning about files they have not developed, which causes the files at risk of turnover measure to degrade. For RevOwnRec, each studied system has a trusted developer circle for the reviews; hence this recommender fails to optimally distribute knowledge and improve files at risk of turnover. Since these reviewers may not be the file owners, the CSR also tends to decrease or not to change considerably.

Table I: Recommender performance vs. reality. Up and down arrows indicate improvement and degradation, respectively.

<table>
<thead>
<tr>
<th>CSR</th>
<th>Project</th>
<th>Expertise</th>
<th>Workload</th>
<th>FaR</th>
<th>CSR</th>
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<td>19.75% ↑</td>
<td>47.78% ↓</td>
<td>-20.94% ↑</td>
<td>-37.07% ↓</td>
</tr>
<tr>
<td>TurnoverRec</td>
<td>Roslyn</td>
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<td>0.67% ↓</td>
<td>-38.33% ↑</td>
<td>-33.51% ↓</td>
</tr>
<tr>
<td></td>
<td>Rust</td>
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<td>-4.38% ↓</td>
<td>-23.66% ↓</td>
<td>-53.43% ↓</td>
</tr>
<tr>
<td></td>
<td>Kubernetes</td>
<td>-25.72% ↓</td>
<td>-0.09% ↑</td>
<td>-30.32% ↓</td>
<td>-44.49% ↓</td>
</tr>
<tr>
<td>Solo</td>
<td>Roslyn</td>
<td>7.38% ↑</td>
<td>4.03% ↓</td>
<td>-34.9% ↑</td>
<td>55.22% ↑</td>
</tr>
<tr>
<td></td>
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<td>4.97% ↑</td>
<td>0% -</td>
<td>-25.42% ↑</td>
<td>73.09% ↑</td>
</tr>
<tr>
<td></td>
<td>Kubernetes</td>
<td>9.42% ↑</td>
<td>1.70% ↓</td>
<td>-28.67% ↑</td>
<td>96.74% ↑</td>
</tr>
</tbody>
</table>
For chRev, the score function is based on xFactor. Hence, the CSR is consistently improved, notably at the cost of limiting the improvement of workload for the core development team in comparison to other recommendation approaches.

For LearnRec, there is no consideration for the retention of recommended candidates, so the files at risk of turnover measure tends to increase because many reviewers leave the project. The suggested reviewers by this recommendation system are not experts, but seek to learn by reviewing the PR, so the CSR measure tends to decrease.

For RetentionRec, the recommender suggests candidates with the most knowledge about the project, not a specific PR. As a result, undesirably, the core developers’ workload increases because they are mostly permanent developers of a project. However, their knowledge causes CSR and expertise to improve.

For TurnoverRec, the recommender favours the most permanent candidates, regardless of the degree of knowledge that they have about the code being modified by a PR. This bias leads to knowledge retention, thus improving files at risk of turnover. However, since distributing knowledge among developers is an important risk mitigation measure, the choice of less knowledgeable candidates causes the CSR to decrease.

For Sofia, when none of the changed files are at risk of turnover, chRev is used. This compensates for expertise and CSR measures that are lost due to knowledge distribution caused by TurnoverRec. However, most of the time, this is at the cost of increasing the workload for the core development team. Sofia uses TurnoverRec for changesets with files at risk of knowledge loss, which has a favourable effect and causes the files at risk of turnover measure to improve.

Figure 2 shows the relation between CSR and files at risk of turnover in our experiments. The bottom-left quadrant shows evidence of a trade-off between CSR and Files At Risk for approaches that optimize only one characteristic. Meanwhile, chRev and Sofia mostly present results in the top-left quadrant. This indicates that they are generally robust to the trade-off between CSR and files at risk of turnover, and can broadly optimize both the risk of knowledge turnover and CSR. Finally, the bottom-right quadrant shows that optimizing for learning opportunities (e.g., using LearnRec) negatively impacts both files at risk of turnover and CSR.

These observations indicate that if there is no deliberate effort to distribute knowledge, as the files at risk of turnover improves, unless the necessary restrictions are put in place, such as a limitation on the most knowledgeable reviewers, the CSR degrade. This decrease, in turn, increases the chance of merging a fix-inducing PR into the project. This suggests that there is an inherent trade-off between the files at risk of turnover and CSR evaluation measures. This does not hold in all cases. For example, in LearnRec, both files at risk of turnover and CSR decreases which is likely because the recommended candidates leave the project as retention is not considered in the score function. Since leavers may leave a gap in the team understanding of an area of the codebase, the files at risk of turnover and CSR measures tend to degrade. For Sofia, the recommender’s candidate scoring function maximizes the expertise of the reviewers unless there is a file with few knowledgeable developers in the changeset. In these cases Sofia tries to distribute knowledge which lessens the core workload and improves the files at risk of turnover. This active effort cancels out the native trade-off and improves both files at risk of turnover and CSR. Sofia works better in terms of fix-inducing code changes, but like other approaches, it does not have any parameter to control the sensitivity to these changes. The inflexibility may become a barrier to adoption for this recommender as it cannot be tuned to suit the needs of users.

The evaluation results indicate that unless active effort is put into knowledge distribution while keeping the expertise high, the CSR and files at risk of turnover have an innate trade-off. In cases where both CSR and files at risk of turnover are maximized, other measures such as core developer workload suffer. Hence, one cannot simultaneously optimize suggested reviewers with respect to the risks of knowledge loss and fix-inducing changes.

**RQ2:** How can the risk of fix-inducing code changes be effectively balanced with other quantities of interest?

To balance the innate trade-off between files at risk of turnover and CSR, we suggest using a hybrid reviewer recommendation approach to optimize the recommendation process based on the PR fix-inducing likelihood. We propose a recommender to improve the CSR when a PR has a high risk of being fix-inducing. The objective function for the proposed Risk Aware Recommender (RAR) is formulated as:

$$RAR(D, R) = \begin{cases} 
Sofia(D, R), & \text{DefectProb}(R) \leq P_D \\
chRev(D, R), & \text{otherwise}
\end{cases}$$

(8)

In this formula, the $P_D$ represents the threshold for the likelihood of PRs to be fix-inducing. If the $P_D$ threshold is exceeded, chRev is used to suggest experts. Otherwise, Sofia will suggest reviewers for the PR. The chRev ranks candidate reviewers based on their familiarity with the changed files while Sofia opportunistically distributes knowledge when the modified files are not at risk of turnover.

**Approach.** We study the performance of RAR in terms of the coreWorkload, files at risk of turnover, expertise, and CSR measures. We also study the impact that varying the $P_D$ threshold from 0.1 to 0.9 has on RAR performance.
Figure 3: The effect of $P_D$ on the performance of RAR for each evaluation metric, on different projects over different quarters.

Results. Figure 3 shows the evaluation measures as the $P_D$ changes for the studied systems.

Analysis. Figure 3 shows that as the value of $P_D$ increases, the tolerance of RAR for fix-inducing PR grows. As a result, we expect more knowledge distribution leading to a decrease in CSR. As fewer experts are assigned to the tasks, the overall expertise also diminishes, which is not an unexpected outcome.

However, there are project-specific trends that are worth noting. For example, Figure 3a shows that the evaluation measures for the Roslyn project are steadily declining as $P_D$ increases, whereas Figure 3c shows that the majority of the impact of varying $P_D$ in the Kubernetes project takes place between $P_D = 0.1$ and $P_D = 0.3$. Moreover, Figure 3b shows that for Rust, the impact of varying $P_D$ is relatively small.

Overall, the Risk Averse Recommender (RAR) yields an average change of 12.48%, 0.93%, -19.39% and 80.00% over different quarters for evaluation measures of Expertise, Core workload, files at risk of turnover and CSR, respectively.

A closer look at the model estimates of the likelihood of fix-inducing changes helps to explain these project-specific trends. Figure 4 shows the distributions of the estimated likelihood of changes being fix inducing stratified by project and quarter for four quarters (The complete distribution can be found in our supporting material’s Figure 1). We observe that, unsurprisingly, larger performance fluctuations in Figure 3 are associated with the $P_D$ values where the majority of the estimated likelihoods lie in Figure 4. Moreover, despite an overall decreasing trend in terms of the likelihood of fix-inducing changes over time, the trend of each quarter is similar to its adjacent quarters. This local similarity may help stakeholders to effectively tune $P_D$ values (see RQ3 for a more detailed analysis).

The RAR settings can be tuned to balance the risks of knowledge loss and fix-inducing changes. Indeed, as the threshold for indicating tolerance of the risk of fix-inducing changes increases, the risk of knowledge loss impacts fewer files. However, identifying the optimal threshold setting requires an awareness of project-specific trends in the model estimates of the likelihood of fix-inducing changes.

RQ3: How can we identify an effective fix-inducing likelihood threshold ($P_D$) interval for a given project?

Our analysis from RQ2 indicates that the performance of the RAR is sensitive to the $P_D$ setting. The effective range of $P_D$ is dependent on the past likelihood of fix-inducing changes. In this question, we seek to propose an approach to help project stakeholders in the selection of effective $P_D$ settings based on their tolerance for the risk of fix-inducing changes.

Approach. We explore the following three approaches to identify effective periods:

- **Static method**: This baseline considers the effective period spans the entire range between 0 and 1.
- **Normalization method**: The effective range spans between upper and lower extremes of the distribution of likelihoods from the prior periods. To match common outlier definitions, we set our lower and upper extremes to $Q_i - 1.5 \times IQR$ and $Q_i + 1.5 \times IQR$, respectively, where $Q_i$ is the ith Quartile, and IQR is the Interquartile range between $Q_1$ and $Q_3$. All examples within the range are normalized by the maximum value.
- **Dynamic method**: A selective variant of the normalization method. Instead of considering all previous periods, we only consider the last six months. This allows the model to focus on the current part of the project life cycle.

For each of these three methods, we simulate three different thresholds: 25% (risk-averse recommendation), 50% (balanced recommendation), and 75% (risk-tolerant recommendation) of the effective period for our three projects in the dataset.

Figure 5: Conover Test results.
Results. Figure 6 shows distributions of relative improvement in CSR that are achieved for different time periods (points) of the studied systems (plot columns) of our approaches (y-axes) in different configurations (plot rows).

Analysis. We use the Friedman test (two-tailed, paired, $\alpha = 0.05$) [50] and apply it to the CSR performance data (Table II). We observe significant differences between the investigated methods in all configurations except for Roslyn in the risk tolerant setting. Next, we use Kendall’s W to determine the magnitude of this effect [51] (Table III). Large and small effects are observed in 55% and 22% of the cases, respectively.

We apply the Conover test to discern which pairs cause this significant difference [52]. Figure 5 shows p-values for different thresholds with red lines indicating the 0.05 confidence interval. The results imply that the dynamic method significantly affects risk-averse ($P_D = 25\%$) and risk-balanced ($P_D = 50\%$) recommendations in all studied systems. For the normalization method, the effect on the results is inconsistent. The dynamic method considers the pivot of the project in various periods, which affects the CSR. In contrast, the normalization method considers the entire history and may not be sensitive enough to react to risk fluctuations as projects age [53].

On the other hand, for risk-tolerant recommendations ($P_D = 75\%$), none of the methods have a consistent effect on the results due to the difference in the distribution of defect proneness for various periods. Roslyn has a high rate of fix-inducing PRs ($P_D > 0.5$) in all the periods, so the approach does not affect the results. However, Kubernetes, which has more fix-inducing PRs in the earlier periods than more recent ones, is affected mainly through a dynamic method.

For risk-averse ($P_D = 25\%$) and risk-balanced ($P_D = 50\%$) recommendations, the dynamic method tends to provide the most value by recommending an effective period while for risk-tolerant recommendation ($P_D = 75\%$), none of the methods outperform others significantly.

VII. PRACTICAL IMPLICATIONS

Below, we summarize what we believe are the practical implications of greatest value for practitioners and researchers.

RQ1) Practitioners can use code review to balance files at risk of abandonment with the risk of fix-inducing changes. Our observations in RQ1 show that if the likelihood of a PR inducing a fix is not considered explicitly as a parameter in the recommenders’ objective function, the recommended reviewers may lack the subject matter expertise to prevent future fixes, and in turn, increase the risk of merging fix-inducing PRs. The results also show an inherent trade-off between some of the evaluation measures, such as files at risk of turnover, and the risk of merging fix-inducing PRs. We propose CSR as a heuristic to assess the degree to which a (recommended) reviewer assignment mitigates the risk of fix-inducing changes.

RQ2, RQ3) RAR can be tuned according to the tolerance of the risk of fix-inducing changes without drastically impacting other properties of interest of the recommended reviewing assignment. Our observations in the first research question indicate that active effort should be made to mitigate the inherent trade-off between CSR and files at risk of turnover. To this end, RAR is proposed, which uses the $P_D$ setting, as the threshold for the likelihood of a PR being fix inducing, to influence the suggested set of reviewers. The results of the second research question illustrate that RAR prevents other evaluation measures from being drastically impacted. The $P_D$ setting can be tuned using a combination of our proposed dynamic method (see RQ3) and input from stakeholders about their tolerance of risk for fix-inducing changes. While project-specific characteristics (e.g., the incidence rate of fix-inducing changes) impact the sensitivity of the approach to the $P_D$ setting, our dynamic approach can be scaled to apply well in different risk tolerance settings.

VIII. THREATS TO VALIDITY

Below, we discuss the threats to the validity of our study.

Construct Validity. Our implementations may contain errors. To mitigate this risk, we augment an existing data set and vetted code from prior work [13] rather than producing our own from scratch. We share our implementation openly to enable the community to audit and build upon our code [54].

It is also possible that CSR does not truly reflect how well fix-inducing code changes are mitigated when assigning reviewers in reality. Because we cannot go back in time and change existing assignments to observe how well CSR truly performs, we evaluate its performance using historical data. We mitigate the chances of CSR being a poor reflection of reality by basing it on proven measurements such as the fix-inducing likelihood and the xFactor [19]. Furthermore, the main idea behind CSR, that experts that have recently interacted with files in a code...
change reduce the likelihood of merging fix-inducing code changes, has been shown to reflect reality in prior studies \cite{42}.

To obtain data at a scale required for this study, we must use automated tools. However, such approaches are not perfect and may induce errors in our results. To prevent any implementation errors, we use an existing tool (Commit Guru). We sampled the tool’s output and manually verified the results. The resulting precision (i.e., 43.9% with confidence=95% and margin=±5%), aligns with prior works \cite{36, 37}. While SZZ may introduce errors into our dataset, our results show that reviewer recommendations can still suggest the most relevant reviewer to reduce fix inducing changes, even when trained on noisy data. Future tools could be used to improve the performance of the approach.

**Internal Validity.** In this study, we consider the effect of assigning experts to review PRs that are potentially fix-inducing using measures, such as CSR. While assigning experts rather than novices to review PRs may change such measures, it does not guarantee that they will actually spot more defects. It is possible that other factors, that do not reflect a reduction in defects, are influencing the changes in CSR. However, prior studies have shown that experts increase the possibility of detecting fix-inducing PRs before merging, we therefore believe that similar outcomes should hold for our study. Further studies might help to clearly identify the impact of reviewers’ experience and CSR on catching bugs during the PR process.

The defect prediction in Rust presents a low balanced accuracy. However, the other two projects yield similar results in different experiments, which we believe voids the possibility of the effect of this low accuracy in our experiments.

**External Validity.** While we apply eight different approaches to three systems, it is possible that our results might not generalize to other approaches or systems. We mitigate this threat by using a large number of approaches and systems with many files and a high volume of PRs. We target such systems because reviewer recommenders are most beneficial in big repositories with many developers. Through this selection we aim to make our findings applicable to the most pertinent systems.

**IX. Conclusions**

In this study, we set out to explore how using a code reviewer recommender to suggest reviewers can affect the risk of defect proneness. To this end, we introduce a new evaluation measure, CSR, and assess seven existing reviewer recommenders against this new measure. Three other measures previously used in the literature are also compared. The results show an inherent trade-off between files at risk of turnover and CSR – improvements to one measure often degrade the performance of the other. To balance this trade-off, an adjustable multi-objective code reviewer recommender, RAR, is proposed. We analyze how RAR can be used to tune the recommendations with respect to the tolerance of the risks of fix-inducing PRs and files at risk of knowledge loss. Our findings suggest that:

- There is a trade-off between knowledge distribution and the likelihood of merged PRs being fix-inducing. However, this trade-off may be resolved by simultaneously optimizing recommendation strategies for both measures. This optimization, in turn, may lead to a decrease of other evaluation measures like core developers’ workload.

- **RAR** can be tuned to balance the risk of knowledge loss and fix-inducing changes by tuning the $P_D$ setting. However, identifying the optimal threshold setting requires an awareness of project-specific trends in the model estimates of the likelihood of fix-inducing changes. The results yield the average change of 12.48%, 0.93%, -19.39% and 80.00% over different quarters for evaluation measures Expertise, Core workload, files at risk of turnover and CSR, respectively. For the proposed measure, CSR, the average change is 73.80%-102.04% for various $P_D$ settings.

- **Project stakeholders** can use **RAR** with a dynamic method for identifying effective range for the $P_D$ setting. The dynamic method provides better performance for risk-averse and risk-balanced reviewer recommendation strategies while not hurting the risk-tolerant strategy’s performance.

In future work, we plan to build an application on top of reviewer recommendation approaches such as **RAR** to study their effect of various in a live environment (e.g., Github). Moreover, we believe that investigating other measurements that estimate the risk of fix-inducing PRs could yield even more suitable candidates for CSR. Future work should also investigate the effects of using inaccurate bug detection methods on the results of reviewer recommenders such as **RAR**. To allow continued progress in this line of inquiry, we have made our code and dataset available online \cite{54}.

Table II: The χ² and p-value results (two degrees of freedom) of the Friedman test applied to the RQ3 values.

<table>
<thead>
<tr>
<th>Project</th>
<th>Threshold</th>
<th>Chi-Square</th>
<th>p-value</th>
<th>Chi-Square</th>
<th>p-value</th>
<th>Chi-Square</th>
<th>p-value</th>
</tr>
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<tbody>
<tr>
<td>Roslyn</td>
<td>25%</td>
<td>10.8</td>
<td>0.00164</td>
<td>12.8</td>
<td>0.00164</td>
<td>12.8</td>
<td>0.00164</td>
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<tr>
<td>Rust</td>
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<td>&lt; 0.001</td>
<td>38.6</td>
<td>&lt; 0.001</td>
<td>15.8</td>
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<tr>
<td>Kubernetes</td>
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<td>16.5</td>
<td>&lt; 0.001</td>
<td>20.6</td>
<td>&lt; 0.001</td>
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Table III: Effect size and magnitude for Kendall’s W (RQ3).

<table>
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<td>Rust</td>
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<td>Kubernetes</td>
<td>25%</td>
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<td>large</td>
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</table>

\[ \chi^2 \] Table IV: The χ² and p-value results (two degrees of freedom) of the Friedman test applied to the RQ3 values.
REFERENCES


[34] anonymous, 2022, supporting online materials. [Online]. Available: https://zenodo.org/record/6727155#


