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Understanding Why and Predicting When Developers Adhere to Code-Quality Standards

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***Abstract*—Static analysis tools are widely used in software development. While research has focused on improving tool accuracy, evidence at Microsoft suggests that developers often consider some accurately detected warnings not worth fixing: what these tools and developers consider to be true positives differs. Thus, improving tool utilization requires understanding when and why developers fix static-analysis warnings.**

We conduct a case study of Microsoft's Banned API Standard used within the company, which describes 195 APIs that can potentially cause vulnerabilities and 142 recommended replacements. We find that developers often (84% of the time) consciously deviate from this standard, specifying their rationale, allowing us to study why and when developers deviate from standards. We then identify 23 factors that correlate with developers using the preferred APIs and build a model that predicts whether the developers would use the preferred or discouraged APIs under different circumstances with 92% accuracy. We also train a model to predict the kind of APIs developers would use in the future based on their past development activity, with 86% accuracy. We outline a series of concrete suggestions static analysis developers can use to prioritize and customize their output, potentially increasing their tools' usefulness.

***Index Terms*—developer-centered static analysis, tools and environments, empirical software engineering**

I. Introduction

Static code analysis is an efficient way to identify software bugs by reasoning about runtime behavior without executing the code. Static analysis tools (SATs) are widely used in both commercial closed-source [9], [51], [66] and open-source [5], [21] development. At Microsoft, teams use SATs to monitor adherence to a variety of code-quality standards, employing engineers to continually improve SATs with state-of-the-art methods. However, studies show that developers tend to fix only a small fraction of the bugs reported by SATs [27], [43]. The common view is that the frequent false-positive warnings these tools report is one of the main reasons developers underutilize the tools [22], [35], [43], [55], [71]. Accordingly, a large research effort [14], [23], [24], [31]–[33], [64], [83], [85] has focused on methods for increasing SATs' accuracy. However, anecdotal evidence at Microsoft shows that *developers often find true-positive warnings not worth fixing*. At Microsoft, teams typically designate developers to analyze a SAT's warnings to select the ones worth fixing. Other developers then either fix the warnings, or explicitly label them as "won't fix", stating their rationale. When we presented a product team with a 95%-accurate SAT for detecting deviations from an important code-quality standard, the team considered only ∼45% of the tool's true-positive warnings as worth fixing. Analyzing **why** the team made these choices, we found that teams often consider fixing warnings in non-production code (e.g., tests) and code not targeting a current ship cycle, as not worth their effort. Further, in some cases, fixing a warning may degrade performance, and so teams elect to violate the standard, but mitigate the associated risks by code reviews and extra safety checks. These observations suggest that making SATs more accurate may not be sufficient to achieve a desired fix rate. In essense, what the teams consider to be true positives differs from what SAT designers traditionally have.

The central goal of this paper is understanding **when** and **why** development teams fix SAT warnings, and developing models that accurately **predict** whether warnings are worth bringing to the developers' attention. These contributions can then lead to concrete suggestions for SAT designers to improve SAT utilization, complementing existing, accuracy-based methods.

Representing the first tangible step toward that goal, this paper performs a case study on a single code quality standard and a single SAT (both used at Microsoft), and develops a machine-learning-based approach for predicting which SAT warnings the developers fix. At Microsoft, teams follow Microsoft's Security Development Lifecycle (SDL) process [48], which consists of a set of practices to develop secure and compliant software. Our study uses Microsoft's Banned API Standard [25], [63], which is part of SDL, and sarif-pattern-matcher [50], which is one of several SAT solutions [49] developed at Microsoft to detect potential violations. (Note that the standard's name is a misnomer. In practice, today, the APIs it describes are merely discouraged rather than banned completely from use. Developers are expected to make reasoned decisions on API use, and, as this paper describes, there exist contexts in which the use of these discouraged APIs is, in fact, acceptable.) The Banned API Standard describes 195 discouraged APIs, which are known to sometimes be unreliable and can cause software vulnerabilities, and 142 preferred C/C++ APIs, which are recommended replacements for the discouraged ones, For example, the standard recommends

[§]Work completed during an internship with Microsoft's 1ES Security Tools Group.

using `strcpy_s`, instead of `strcpy` as the latter can result in buffer overflows [12].

Banned API Standard and sarif-pattern-matcher are well-suited for our study for three reasons:

First, sarif-pattern-matcher is highly accurate for this standard. It is developed by Microsoft software quality assurance experts and has very few false positives, and properly hides warnings in natural language and in commented-out source. Improving the accuracy of SATs is orthogonal (but complementary) to our study's goals, making this standard with an existing accurate SAT a good case study candidate.

Second, a large number of teams at Microsoft are expected to follow this standard. Our analysis of 119,869 repositories finds that 9,021 repositories use the Banned API Standard (the main limiting factor is the standard's applicability only to C/C++). As violating the standard is known to cause critical security vulnerabilities [72], teams consider the standard very seriously. Our analysis is limited to 162 of the 9,021 repositories that are actively maintained, have at least 100 source files and 1,000 commits, and have more contributions from internal Microsoft developers than external open-source developers. These 162 repositories have code contributions from around 15,000 developers, and belong to 49 projects from 15 diverse teams at Microsoft.

Third, developers surprisingly often (84% of the time) chose to deviate from this standard and use discouraged APIs, with justification, providing ample opportunities to understand developer reasoning. In the 162 repositories, we detected 479,987 discouraged and 93,663 preferred API usages (573,650 total) associated with 3,137 developers.

This observation suggests that the vast majority of the warnings sarif-pattern-matcher reports, despite seemingly being true positives, in fact, do not result in code improvements. These uses of discouraged APIs enable us to understand developer reasoning toward improving the SAT. The developers make their decisions based on assessed risk, the availability of a safe API alternative, and the complexity of correctly using that API. For example, we find that teams tend to adhere to the standard more in code that is under active development and less in code borrowed from other projects. When reusing legacy code with discouraged APIs, developers elect to implement additional safety checks rather than reimplementing that legacy functionality using preferred APIs. Further, teams use preferred APIs more in non-test code and source files that involve more editing and have multiple contributors. With the goal of understanding such intricacies of API usages toward improving SAT design, we identify and analyze 25 factors that encode the circumstances in which teams implement code-quality standards. We use these factors to model and predict warning usefulness. This can allow SATs to prioritize and customize their warnings by considering the development context, improving their utility in the development process.

While our analysis focuses on this one standard, the methodology we describe should generalize to other code-quality standards and SATs, as both the methodology and the 25 factors are agnostic of the standard.

To make our study possible, we extend sarif-pattern-matcher to also detect preferred API call sites, to trace relevant developer information, and to perform temporal analysis. In addition to analyzing the 162 repositories, we do a deeper, temporal case study on one repository over a 10-year span. We answer three research questions:

RQ1: What factors correlate with development teams' adherence to the Banned API Standard?
Answer: Complexity of the project, work environment, whether the code was under active development or non-shipping, developer's coding experience, and whether a developer is an internal or an external employee.

RQ2: Can the correlated factors predict adherence to the Banned API Standard?
Answer: An artificial-neural-network (ANN)-based model can predict whether development teams will use preferred or discouraged APIs with 92% accuracy.

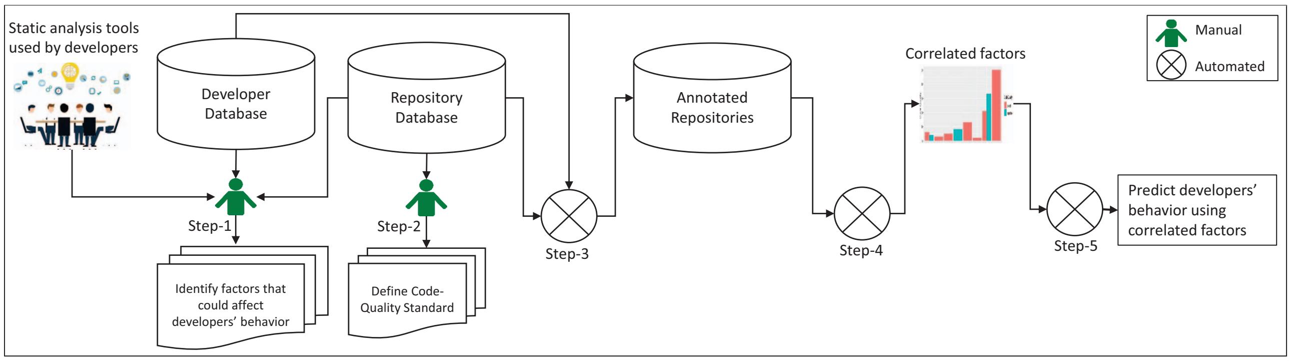
RQ3: Can development team's past activity, encoded in terms of correlated factors, predict future standard adherence?
Answer: An ANN-based model trained on past behavior can predict whether team will use preferred or discouraged APIs in the future with 86% accuracy.

SATs designed to detect usage of specific APIs can use these prediction models to prioritize and customize their warnings, improving utilization. Our findings drive our concrete recommendations for improving SATs:

1) SATs can prioritize the warnings the developers are more likely to address. For example, our analysis showed that developers are more likely to address violations in production code, and for some operations (e.g., stream buffering) than for others (e.g., memory copy), often for performance reasons. By prioritizing violations developers are likely to fix, SATs can ensure developers see more of the warnings they will act on, earlier.
2) SATs can customize warnings to include suggestions on how to address them, to improve developer compliance. For example, our analysis found that for discouraged APIs in reused legacy code, developers often opted to add safety checks instead of replacing those APIs.
3) SATs can customize warning content based on who is using them. Our analysis showed that more experienced developers used more preferred APIs and may need only a simple prompt to fix discouraged APIs. However, novice developers may need to see more context about the associated risks and potential solutions. A SAT can also suggest code reviews when it believes other developers would fix a warning left unfixed.
4) Team culture plays an important role in API use, which can help customize SATs. For example, SATs could raise an alarm if a team fails to follow a standard when other teams likely would have, or allow a team to consciously limit the warnings to those of the highest priority.

II. Background

SATs reason about program behavior without running the program. They typically combine different kinds of analy-



Static analysis tools used by developers
Developer Database
Repository Database
Annotated Repositories
Correlated factors
Manual
Automated
Step-1
Step-2
Step-3
Step-4
Step-5
Identify factors that could affect developers' behavior
Define Code-Quality Standard
Predict developers' behavior using correlated factors

Fig. 1: End-to-end methodology to determine what factors could influence development teams' adherence to code-quality standards and to predict this behavior from the identified factors.

ses that consist of independent rules. Each rule describes a requirement that correct, high-quality code should meet. A set of rules constitutes a code-quality standard. If the tool encounters code that violates a rule, it reports a warning. It is up to the developer to decide whether the warning is real and worth addressing. In practice, SATs can detect software bugs and vulnerabilities that range from purely syntactic ones [26] to complex semantic ones that can be used to perform program optimization [2] and fix security vulnerabilities [65]. However, the warnings produced by SATs are often coarse-grained because they over-approximate program behavior to encompass all possible inputs [44]. To address this, researchers have explored the kinds of bugs that SATs can accurately detect [22], [75] and the kinds of bugs developers tend to fix, along with the time they take to fix them [27], [43], [45], and methods to suggest automated fixes [40], [45].

Even though SATs provide several benefits, there exists ample evidence that these tools are underutilized by developers [27], [40], [43]. A lack of accuracy (i.e., a high percentage of false-positive warnings) and the manual effort required for comprehending warnings to identify bugs that are worth fixing are the two main issues that complicate the adoption of SATs [43], [71]. Accordingly, a large research effort has focused on methods for increasing SATs' accuracy [14], [23], [24], [31]–[33], [64], [83], [85]. These approaches consider different aspects of a SAT's warning, including factors related to source code [23], [39], [85], repository history [80], and historical data about fixing warnings [34] to detect true-positive warnings. Further, researchers have also proposed ways to automatically generate the fixes for the true-positive warnings [40], [44]. A recent study, which is closest to our work, investigates how developers use SATs in different development contexts defined in terms of the coding activity (e.g., code review, local programming, continuous integration), types of SAT warnings (e.g., naming convention, logic, concurrency), and whether developers update the configuration of SATs [77]. Their findings aim to produce novel automated strategies to help developers pay attention to the right warnings depending on the context they are in. Our proposed approach to help SATs prioritize their true-positive warnings considering factors that influence developers' decision to act on them complements these existing studies.

III. Methodology

Figure 1 shows our study's five-step methodology.

Step-1: Enumerate factors that may influence development teams' adherence to code-quality standards. To identify the factors that can be objectively measured and could influence development teams' adherence to code-quality standards in a general software development setting, we analyzed (a) what SATs Microsoft teams use in their workflow, (b) the information available about developers in Microsoft's developer database, and (c) the meta-data of 119K+ repositories stored in Microsoft's repository database. We also considered the 23 "Golden Features," the most important features for detecting actionable warnings identified by Wang et al. [78] by performing a systematic evaluation of the features (or factors) that have been proposed in the literature to improve SAT's accuracy. Figure 2 shows the 25 factors our analysis identified along with their computation method. To help the reader, we sort these factors into three categories — developer, code base, and quality standard — based on the information sources used to derive the factor. In general, these factors measure developers' expertise, the complexity of development tasks, work environment, and development teams' motivation for adhering to a code-quality standard. Note that the process of identifying these factors and the factors themselves are agnostic of the Banned API Standard, and thus can generalize to other standards and SATs. Further, note that all of the 25 factors may/may not affect developers' adherence to a selected standard. In Step-4, we describe how to identify the factors that are associated with the standard of interest.

Step-2: Define code-quality standard, extend SAT to detect bugs and fixes along with their authors, and compute factors. To perform the analysis, we first had to define a code-quality standard that can be verified using a SAT. This involves carefully crafting rules (code patterns) to accurately detect code that adheres to or deviates from the code-quality standard. Currently, SATs only use rules to detect the violation

Factor	Description	Computation Method	Data Type
	Factors Derived from Developer Information		
CareerStageName	designation of the developer	computed from developer database	categorical
YearsOfMSExperience	number of years developer has worked at Microsoft (excluding the duration between the time when a developer left and rejoined the company)	computed using developers leaving and joining (or re-joining) dates	numerical
EmployeeLevel	position of developer in organization hierarchy (CEO is 1 and other junior employees have higher values)	computed from developer database	numerical
JobTitleName	job category that classifies developer's designation (e.g., *Service Engineering, Software Engineering, Program Management, Technical Delivery*)	computed from developer database	categorical
StandardTitle	type of role within a job category that a developer is occupying (e.g. *Senior Service Engineer, Software Development Engineer, Consultant*)	computed from developer database	categorical
AuthorChurn	a developer's code churn in a repository. This varies from $[-1, 1]$ and negative value indicates that developer rewrites her code more often.	$(LOC_i - LOC_d)/(LOC_i + LOC_d)$ where LOC_i and LOC_d denote the lines of code inserted and deleted by a developer, respectively	numerical
WorkLocation	country where the development team is located	computed from developer database	categorical
Department	department (e.g., *Canvas SKI Eng*) to which developer belongs	computed from developer database	categorical
ProjectType	type of the project (e.g., *OCAS Word*) assigned to developer	computed from developer database	categorical
ProjectName	project (e.g., *OCAS-Word iOS/Mac*) assigned to developer	computed from developer database	categorical
IsInternalMSEmployee	whether developer is an internal (*true*) or external (*false*) Microsoft employee	computed from developer meta-data	dichotomous
EmployeeType	whether a developer is *full-time* employee, contract-based *vendor*, or other (e.g. intern)	computed from developer meta-data	categorical
	Factors Derived from Code Base Information		
SourceLOC	number of source code lines in a source file excluding comments	implemented sarif-pattern-matcher module to parse source files and count lines excluding comments	numerical
RepoLOC	number of source code lines in a repository excluding comments	implemented sarif-pattern-matcher module to count the lines of code in all source files in repository	numerical
FileChurn	how often the source file is modified by developers. This varies from $[0, 1]$ and lower value indicates that file is modified more often.	$abs(LOC_i - LOC_d)/(LOC_i + LOC_d)$ where LOC_i and LOC_d denote the lines of code inserted and deleted in a source file, respectively	numerical
SourceIntermittentChanges	Number of developers who have contributed to a source file prior to a given commit	computed by parsing the commit history of source file to identify distinct developers	numerical
TeamSize	number of peers of a developer who report to same manager	computed using developer database	numerical
RepositoryOrganization	the product umbrella to which a repository belongs (e.g., *office*)	obtained from repository database	categorical
RepositoryProject	the project (within a product umbrella) to which the repository belongs (e.g., *OC*, *OE* under *office*)	obtained from repository database	categorical
Repository	the code base to which a developer contributes and implements code quality standards (e.g., *Office-Performance-HUD* under *OE*)	obtained from repository database	categorical
IsTestCode	whether the source file is a test code (*true*) or not (*false*)	computed by parsing and matching patterns in the source file enlistment path	dichotomous
IsActiveCode	whether the source file is under active development (*true*) or an external dependency (*false*)	computed by parsing the commit history. An active source file should have at least one commit that involves non-zero insertions/deletions that are less than the total LOC of the file.	dichotomous
	Factors Derived from Quality Standard Information		
RuleType	conceptual topic to which a code-quality standard rule belongs (e.g., APIs in Banned API Standard related to *string copying*)	manually analyzed quality standard rules to categorize them into conceptual topics	categorical
QualityStandardApplicability	prevalence of distinct code-quality standard rules in a repository	fraction of #distinct rules detected and total #rules defined in the quality standard	numerical
QualityStandardDensity	prevalence of code-quality standard in a repository	fraction of #rules detected and total LOC	numerical

Fig. 2: Factors that can influence development teams' adherence to code-quality standards.

of rules. However if code does not violate any rule, that does not imply that it follows all rules because it is possible that the code may not implement any quality standard rule. Thus, there is a need to create rules to explicitly detect code that *does* follows the quality standard, but this can be challenging for complex quality standards. Further, we need to extend SAT to trace the developers who violated or adhered to the quality standard rules to compute factors.

The Banned API Standard [25], [63] describes 195 discouraged APIs and 142 preferred APIs used as a replacement for the discouraged APIs. The discouraged APIs are known to, in some situations, cause severe vulnerabilities, such as remote code execution, local elevation of privilege, arbitrary code execution, and system compromise. Therefore, all development teams are recommended to use the preferred APIs, wherever applicable. For example, the standard recommends using `strcpy_s, wcscpy_s, _mbscpy_s`, instead of `strcpy, wcscpy, _mbscpy`, respectively, which can cause buffer overruns.

We extended sarif-pattern-matcher [50], Microsoft's open-source SAT solution for detecting deviations from the Banned API Standard in three ways. First, we augmented the existing set of rules that detect discouraged API use with new rules to detect preferred APIs. This required creating regular-expression-based patterns with criteria to minimize false positives (e.g., excluding API detection in commented out source code and natural language code comments). Second, using Git blame [13], we identified the developer who used the detected preferred or discouraged API. Third, we performed historical, temporal scanning of a code base for a given time duration (specified using a start and end dates) at a given fixed time interval. Finally, with help of an Microsoft data mining expert, we mined developer and source code metadata from the developer and repository databases using the Kusto query language [11] to compute the 25 factors (recall Figure 2) associated with each detected API use and annotated the API use with the computed factors. As developer behavior can change over time, we computed these factors at the instant the developers used the detected API, approximated with the time-stamp of the containing commit.

Step-3: Execute sarif-pattern-matcher to identify repositories of interest. We executed sarif-pattern-matcher on 119,869 repositories, which include large product repositories, such as Microsoft Windows, Microsoft Office, Skype, and Bing, as well as small prototype repositories. sarif-pattern-matcher found 9,021 repositories that use at least one of the 337 APIs defined by the Banned API Standard. From the 9,021 repositories, we selected the 162 repositories that have: (1) at least 100 #source files (to ensure that it is not a toy repository), (2) at least 1,000 #commits (to ensure that repository has sufficient development history), (3) more contributions from internal Microsoft developers than the external open-source developers (to ensure that majority of developers know about the Banned API Standard), and (4) an associated product or service that is under active development or maintenance (to ensure that repository is not deprecated). These 162 repositories have contributions made by more than 15,000 developers and belong to 15 diverse product teams at Microsoft. sarif-pattern-matcher detected a total of 573,651 (93,675 preferred and 479,976 discouraged) API usages in these 162 repositories from 3,302 developers. We next annotated each API usage with all the factors (recall Figure 2). While annotating, we found that values for many developer-specific factors, such as *CareerStageName*, *EmployeeLevel*, and *Department*, were either marked as "unknown" or stored in private repositories

Factor	**# of Distinct Values**	
	all cases	**complete cases**
CareerStageName	15	13
YearsOfMSExperience	36	31
EmployeeLevel	9	5
JobTitleName	19	10
StandardTitle	62	16
AuthornChurn	1,278	463
WorkLocation	20	11
Department	241	142
ProjectType	531	86
PositionName	260	154
IsInternalMSEmployee	2	1
EmployeeType	3	1
SourceLOC	3,299	1,419
RepoLOC	161	91
FileChurn	1,105	788
SourceIntermittentChanges	79	68
TeamSize	49	40
RepositoryOrganization	15	12
RepositoryProject	49	26
Repository	162	91
IsTestCode	2	2
IsActiveCode	2	2
RuleType	19	18
QualityStandardApplicability	82	61
QualityStandardDensity	36	24

Fig. 3: Diversity in terms of distinct values for factors in the annotated dataset of 162 repositories that contain 573,651 APIs defined by the Banned API Standard. "All Cases" shows the diversity in all of the annotated APIs while "complete cases" shows the diversity in 27,136 subset of APIs for which all of the factors are annotated successfully.

to which we did not have access. Figure 3 ("all cases") shows the diversity, in terms of the number of distinct values obtained for each factor after annotating the 573,651 API usages. Figure 3 "complete cases" shows the diversity of factors in the 27,136 subset of API usages for which all of the factors were annotated successfully. While conducting the statistical analysis, as described in Step-4, we considered the API usages for which the required factors were annotated successfully. While conducting the prediction analysis, as described in Step-5, we used complete cases of the annotated dataset, which contains sufficient data to conduct the analysis.

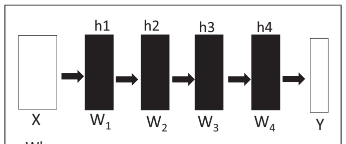
Step-4: Empirically measure which factors correlate with development teams' adherence to the code-quality standards. We represented development teams' choice to use a preferred or discouraged API as a binary dependent variable. Numerically, we used "1" for "preferred" and "0" for "discouraged". Depending on each factor's data type (see Figure 2), we measured its correlation with development teams' choice of preferred or discouraged APIs using the appropriate nonparametric statistical tests, which do not make any assumptions on the underlying distribution of the data.

For each categorical or dichotomous factor, we created a $n \times 2$ contingency table where n represents the number of distinct values the factor can take. For each value, the table contains the distribution of preferred and discouraged API usage by developers. We then ran a *Chi-Square test of independence* [46] on the contingency table to see if the development teams' choice to use preferred or discouraged APIs is independent of that factor. The Chi-Square test computes a p-value (p) that indicates whether our null hypothesis (a developers choice to use a preferred or discouraged APIs is independent of the factor) should be rejected. For each numerical factor, we split the distribution of that factor's values into two distribution samples: (1) the distribution of the factor's values for which developers used preferred APIs, and (2) the distribution of the factor's values for which developers used discouraged APIs. We used *Mann-Whitney U test* [47], which measures rank biserial correlation [19] to determine if the difference between the two distribution samples was statistically significant. That is, the test computes a p-value (p) that indicates whether our null hypothesis (the two distribution samples are statistically indistinguishable) should be rejected. If the two distribution samples are statistically distinguishable, it indicates that the development teams' adherence correlates with that factor.

We used the standard criteria for statistical significance, $p \leq 0.05$, to mean the factor correlates with development teams' adherence, and $p > 0.1$ to mean the factor does not correlate. We also computed the effect size (*es*) i.e., the strength of the correlations using *Cramèrs' V* [42] for categorical and dichotomous factors, and *Somers' D* [57] for numerical factors. While Cramèrs' V $\in \{0, 1\}$, Somers' D $\in \{-1, 1\}$. As per Gignac et al. [18], we mapped effect size values to adjectives: very weak ($|es| < 0.1$), weak ($0.1 \leq |es| < 0.2$), moderate ($0.2 \leq |es| < 0.3$), and strong ($0.3 \leq |es|$). To verify that correlations observed were not arbitrary, we computed the *95% confidence interval* (CI) that tells us the range of the effect size with 95% confidence. We therefore considered correlations to be statistically significant when $p \leq 0.05$ *and* 95% CI does not span 0.

Step-5: Predict adherence to the code-quality standard from correlated factors. We formulated the problem of predicting development teams' adherence to the code-quality standard from correlated factors as follows: Let $F_1, F_2, ..., F_n$ represent the n independent factors that influence development teams' adherence to the quality standard, and let y represent the binary dependent variable indicating whether the team adhered to ($y = 1$) or deviated from ($y = 0$) the quality standard. Our goal was to compute a function $f(F_1, F_2, ..., F_n)$ that evaluates to $P(y = 1)$, which is the probability that a team will adhere to the quality standard. In the case of the Banned API Standard, $P(y = 1)$ represents team decides to use a preferred API.

To solve this problem, we experimented using the logistic regression and artificial neural network (ANN) [73] models, and found that ANN performed better than logistic regression. We trained and evaluated a five-layer ANN model consisting of four hidden layers (h1 and h3 as dense while h2 and h4 as dropout layers) and one output layer that used non-linear factor combinations of *sigmoid* and *relu* functions to learn and predict adherence to the Banned API Standard. We used *sigmoid* for the outermost hidden layer because its output is a value between 0 and 1, making it useful for binary classification; we used *relu* for inner hidden layers because the fast computation made the model more efficient. Figure 4 shows the model's architecture, along with its parameters and the non-linear functions it uses. The model's input is a matrix whose columns represent multiple factors and each row represents a development context (encoded in terms of the factors) in which teams used preferred or discouraged APIs. The model combines multiple factors using non-linear functions to compute the output matrix that contains the probability that a team would use a preferred API for each row of the input matrix. The model used supervised learning with a training and a test phase. During the training phase, the model took as input both the input matrix and the expected team choice to use a preferred or discouraged API (*ground truth*), and learned the parameters (values of hidden layers) to predict the ground truth from the given factors. To ensure that the model did not over-fit on the training set, it was validated on a fraction of the training set (i.e., the validation set) that was not used for learning. If a model's accuracy on the validation set started to decrease, it starts to over-fit on the training set. The model was trained until the max number of epochs were reached or the model started to over-fit. During the test phase, the trained model took as input only the matrix and output the probability of teams' choice to use preferred ($P(y = 1)$) or discouraged ($P(y = 0)$) APIs for each row in the input matrix. We considered $P(y = 1) > 0.5$ to imply that a team will use a preferred API.



Where:

$Y = sigmoid(W_4\, relu\left(W_3(W_2\, relu(XW_1))\right))$

$sigmoid(x) = {}^{1}/_{1+e^{-x}}$	X : bs x n
$relu(x) = max(0, x)$	W_1 : n x 256
batch size (bs) = 64	W_2 : 256 x bs
#factors (n) = 23	W_3 : bs x 128
h1, h3: hidden dense	W_4 : 128 x 2
h2, h4: hidden dropout	Y : bs x 2

Fig. 4: The architecture of the artificial neural network model used to predict development teams' adherence to code-quality standards for given factors. "bs" and "n" denote the batch size and the number of factors used for prediction, respectively.

We evaluated the ANN model under the following two scenarios: (1) **Analysis over code bases.** This scenario considered the dataset of annotated API usages from all 162 repositories and used uniform random sampling to create training and test sets that were representative of all repositories. (2) **Analysis across time.** This scenario considered the dataset of annotated API usages detected from the case study repository at fixed time intervals (15 days) starting from July 15, 2011 and ending on Sept 30, 2021. (Our analysis uses fixed time intervals instead of every commit for performance reasons. Analyzing every commit over 10 years would require executing the SAT on $\sim 25,000$ revisions; our analysis handled $\sim 2,400$ revisions.) The training set consisted of annotated API usages detected before April 30, 2020, and the test set consisted of API usages detected on or after April 30, 2020. The model learned from the development team's past API usage to predict their behavior in terms of using preferred or discouraged APIs in the future. The hyper-parameters used for training the models were: batch size = 64; validation split = 0.3; decaying learning rate (lr) starting from 0.001 and decaying by a factor of 0.1; dropout rate (h2) = 0.4; dropout rate (h4) = 0.3; loss function = binary cross entropy; optimizer = adam.

IV. Evaluation

This section answers three research questions about the developers' adherence to the Banned API Standard, first describing the dataset and metrics used to answer these questions.

A. Dataset

Correlation Analysis. To identify correlations between each factor and development teams' adherence to the Banned API Standard, we used the dataset of 573,651 API usages in 162 repositories annotated with 25 factors listed in Figure 2. As not all APIs could be annotated with all the factors (recall Step-3 in Section III), to analyze the correlation between a factor and development teams' adherence to the Banned API Standard, we used a subset of the API usages that could be annotated with that factor. While presenting correlation results, we present the distribution of preferred and discouraged API usages annotated with that factor.

Prediction over code bases. To make predictions about development teams' adherence to Banned API Standard, we used the subset of 27,309 API usages that could be annotated with *all* 23 of the correlated factors (with > 1 distinct values in Figure 3 ("complete cases") and with $p < 0.05$ in Figure 5). We split this dataset into a training set consisting of 19,117 API usages ($\sim 70\%$) and a test set, which consisting of 8,192 API usages ($\sim 30\%$). To do this, we randomly sampled the API usages from each class (preferred and discouraged) to ensure that the overall class distribution ($\sim 20\%$ preferred and $\sim 80\%$ discouraged) was preserved in the training and test sets. To prevent classification bias, we used the Synthetic Minority Oversampling Technique (SMOTE) [10], a technique to balance training sets, to balance the distribution of preferred and discouraged APIs in the training set. This increased the training set size from 19,117 to 27,545 with $\sim 43\%$ preferred and $\sim 57\%$ discouraged API usages. Note that it is challenging for techniques like SMOTE to exactly balance the distribution of the two kinds of API usages. To address the remaining slight imbalance, we used additional evaluation metrics, as described in Section IV-B, to assess the performance of trained models.

Prediction across time. To make predictions about development team's use of preferred or discouraged APIs in the future using the factors that encode their past API usage, we use the case study repository that has been under active development since July 5, 2011. We used sarif-pattern-matcher to scan this repository at an interval of 15 days starting from July 15, 2011 to Sept 30, 2021. For each time-stamp, the API usages detected by sarif-pattern-matcher were annotated with the factor values computed for that time-stamp, as these values can change over time. sarif-pattern-matcher detected a total of 199,872 API usages (143,287 discouraged and 56,585 preferred) across 170 timestamps. We split the dataset into before/after a single timestamp of April 30, 2020, such that all annotated API usages before this date comprise the training set and all usages on or after the selected date comprise the test set. This resulted in 140,188 API usages ($\sim 70\%$) in the training set and 59,684 ($\sim 30\%$) in the test set. As many of the factors remain constant for a single repository, for this analysis we used the 7 factors ("AuthorChurn", "SourceLOC", "IsActiveCode", "IsTestCode", "RuleType", "FileChurn", and "SourceIntermittentChanges") that change more frequently over time along with the path of source files. Finally, we used SMOTE [10] to balance the distribution of preferred and discouraged API usages that resulted in a training set of 283,150 API usages with $\sim 43\%$ preferred and $\sim 57\%$ discouraged APIs.

B. Evaluation Metrics

To measure correlation between individual factors and development teams' adherence to the Banned API Standard, we use the *p-value*, *effect size*, and *95% CI* computed for that factor using appropriate statistical tests (see Step-4 in Section III). We consider a correlation to be statistically significant if $p < 0.05$ and 95% CI does not span 0. We evaluate prediction models using the following metrics.

1) **Accuracy**: The ratio of correct predictions to all predictions (note that predicting adherence is equally important as predicting deviation for improving SAT's utilization).
2) **95% CI**: The range of *Accuracy* with 95% confidence.
3) **AUC-ROC**: Area under the ROC curve, which gives the average accuracy of correctly predicting *preferred* API usages and *discouraged* API usages. This varies from 0 to 1, where 1 corresponds to 100% accuracy. A value between 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is excellent, and more than 0.9 is outstanding [41].
4) **Confusion Matrix**: A matrix to visualize the model predictions and analyze the errors.

C. Results

RQ1: What factors correlate with development teams' adherence to the Banned API Standard?

Factor	Overall Distribution preferred	Overall Distribution discouraged	Correlation r	Correlation 95% CI	Correlation p
CareerStageName*	$20,175$	$116,592$	0.058	$[\ 0.051,\ 0.068]$	ϵ
YearsOfMSExperience$^\oplus$	$50,657$	$245,438$	0.068	$[\ 0.062,\ 0.074]$	ϵ
EmployeeLevel$^\oplus$	$72,069$	$356,884$	-0.104	$[-0.108, -0.099]$	ϵ
JobTitleName*	$69,120$	$352,176$	0.080	$[\ 0.077,\ 0.083]$	ϵ
StandardTitle*	$69,092$	$351,920$	0.147	$[\ 0.144,\ 0.150]$	ϵ
AuthorChurn$^\oplus$	$80,243$	$428,150$	-0.109	$[-0.113, -0.105]$	ϵ
WorkLocation*	$9,779$	$54,943$	0.204	$[\ 0.189,\ 0.220]$	ϵ
Department*	$9,543$	$53,330$	0.447	$[\ 0.438,\ 0.463]$	ϵ
ProjectType*	$22,451$	$109,393$	0.367	$[\ 0.361,\ 0.377]$	ϵ
ProjectName*	$23,190$	$136,527$	0.407	$[\ 0.403,\ 0.417]$	ϵ
IsInternalMSEmployee*	$93,663$	$479,946$	0.025	$[\ 0.023,\ 0.028]$	ϵ
EmployeeType*	$9,793$	$55,368$	0.009	$[\ 0.001,\ 0.022]$	0.141
SourceLOC$^\oplus$	$93,073$	$473,892$	-0.018	$[-0.022, -0.015]$	ϵ
RepoLOC$^\oplus$	$93,675$	$479,976$	-0.064	$[-0.068, -0.060]$	ϵ
FileChurn$^\oplus$	$93,423$	$478,562$	0.137	$[\ 0.134,\ 0.141]$	ϵ
SourceIntermittentChanges$^\oplus$	$78,473$	$394,409$	0.061	$[\ 0.058,\ 0.064]$	ϵ
TeamSize$^\oplus$	$71,925$	$356,287$	0.003	$[-0.002,\ 0.008]$	0.167
RepositoryOrganization*	$93,675$	$479,969$	0.117	$[\ 0.114,\ 0.120]$	ϵ
RepositoryProject*	$93,667$	$479,437$	0.190	$[\ 0.187,\ 0.193]$	ϵ
Repository*	$93,612$	$478,372$	0.330	$[\ 0.328,\ 0.333]$	ϵ
IsTestCode*	$93,073$	$473,892$	0.064	$[\ 0.061,\ 0.066]$	ϵ
IsActiveCode*	$93,675$	$479,976$	0.065	$[\ 0.062,\ 0.068]$	ϵ
RuleType*	$93,670$	$479,974$	0.480	$[\ 0.477,\ 0.483]$	ϵ
QualityStandardApplicability$^\oplus$	$93,675$	$479,976$	0.023	$[\ 0.019,\ 0.027]$	ϵ
QualityStandardDensity$^\oplus$	$93,675$	$479,976$	-0.087	$[-0.091, -0.083]$	ϵ

$\star$: categorical or dichotomous factor; $\oplus$: numerical factor.

Fig. 5: Statistical test results for correlation between factors and development teams' adherence to the Banned API Standard. "Overall Distribution" is the distribution of preferred and discouraged API use per factor. "r" is the correlation strength, from very weak ($|r| < 0.1$) to strong ($|r| > 0.3$), while "95% CI" is the range of "r" with 95% confidence. For the p values, we report ϵ whenever $p < 2.2\times10^{-16}$ because that is the lower bound allowed by R in p value computation.

Figure 5 lists the correlations between each factor (Figure 2) and development teams' adherence to the Banned API Standard. All but two factors (*TeamSize* and *EmployeeType*) had a statistically significant ($p < 0.05$ and 95% CI does not span 0) correlation.

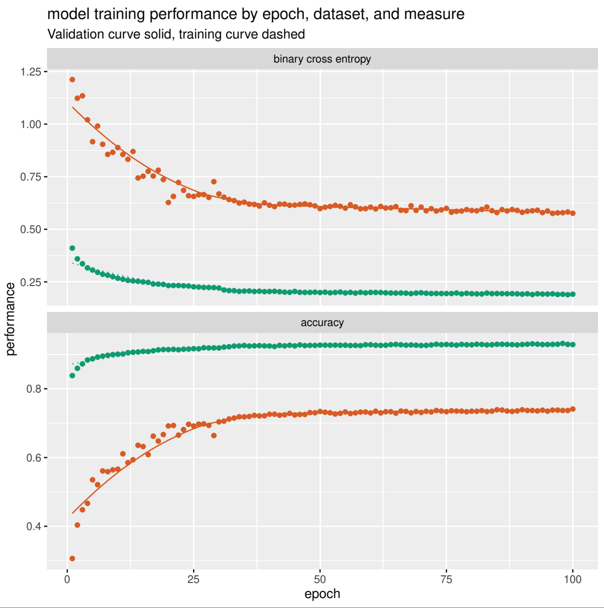
For categorical factors, we analyzed the distribution of preferred and discouraged API usages across factor values to identify *when* development teams tend to use each kind of APIs. For example, analyzing the distribution across the 19 values of *RuleType*, we found that teams are more likely to use *preferred* APIs for "path manipulation", "stream buffering", "string concatenation", "string copy", and "string parsing" operations, while they are more likely to use *discouraged* APIs for "string formatting", "string length", "memory copy", and "string conversion" operations. We did a manual investigation into a set of randomly selected discouraged API usages and reviewed the related artifacts to investigate *why* these choices were made. Our analysis revealed that in certain scenarios teams used the discouraged APIs for performance reasons and implemented additional checks in their code. Similarly, analysis of other categorical factors revealed that more experienced developers (indicated by specific values of *CareerStageName*, *JobTitleName*, and *StandardTitleName*) tend to use more preferred APIs. These results are consistent with prior studies [3], [76] that show that developers with more experience and expertise tend to write high-quality code. Similarly, we found that teams were more likely to adhere to the Banned API Standard if they were associated with specific geographical locations (*WorkLocation*), departments (*Department*), projects (*ProjectType* and *ProjectName*) and products (*RepositoryOrganization*, *RepositoryProject*, and *Repository*). This indicates that adherence can be consistent within teams but can differ across teams within the company and these results corroborate the findings of Lavallée et at. [36]. Due to non-disclosure agreement, we can not share the specific factor values associated with developer or product related details that were found to be associated with use of discouraged and preferred APIs. Finally, teams tend to use more preferred APIs in their non-test code (*IsTestCode*) and code that is under active development or maintenance (*IsActiveCode*) than in the external code borrowed from other projects. Our qualitative analysis of these findings suggests teams behave this way because test code is rarely shipped and therefore considered less relevant, especially when chasing a release deadline. External code was left as-is to avoid conflicts with updates outside of their control.

Statistical tests for numeric factors revealed how adherence to the Banned API Standard can be influenced by changing factor values. For example, a very weak positive correlation was observed for *YearsOfMSExperience*, suggesting that developers who have worked at Microsoft longer are slightly more likely to use preferred APIs. On the other hand, a weak negative correlation observed for *EmployeeLevel* indicates that junior developers, whose *EmployeeLevel* is higher, are likely to use more discouraged APIs. Similarly, we found that developers who edit less code (*AuthorChurn*) or work on large code bases (*SourceLOC* and *RepoLOC*) tend to use more discouraged APIs, while developers who work on source files that involve a lot of changes (*FileChurn*) and have multiple developers working on them (*SourceIntermittentChanges*) tend to use more preferred APIs. Some of these correlations observed (e.g., for *SourceLOC* and *AuthorChurn*) are consistent with the prior studies [61], [62].

Factors related to developers' coding experience (role, years of experience, career stage, author churn), complexity (code base size, number of contributors to the source file, file churn), work environment (department, team, project, work location), motivation to adhere to a code-quality standard (test vs. non-test code, and external vs. internal code), and whether the developer is an internal or an external employee significantly correlate with development teams' adherence to the Banned API Standard.

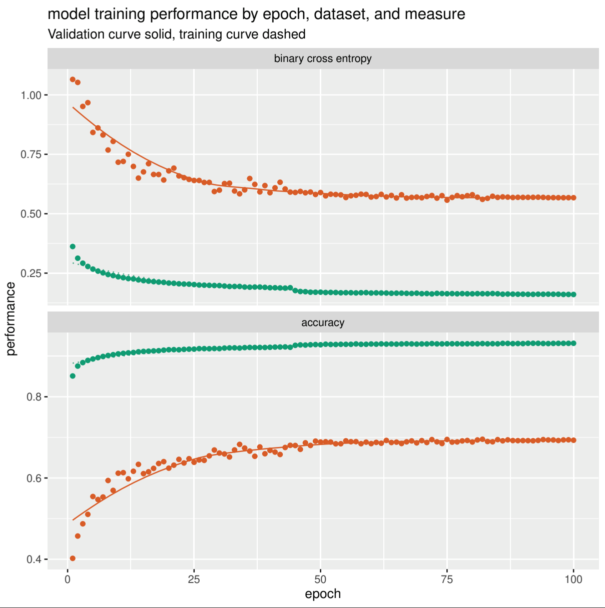
RQ2: Can the correlated factors predict adherence to the Banned API Standard?

The graphs at the top of Figure 6 show the ANN model's performance for 100 epochs on the training set. As shown, loss decreases and accuracy increases on the training and validation sets with increasing epochs and the convergence is achieved after $\sim$85 epochs. After 100 epochs, the accuracy obtained on the training set is 93.40% and 77.41% for the validation set.



Confusion Matrix			Evaluation Metrics	
	reference			
prediction	preferred	discouraged	Accuracy:	0.9175
preferred	1,194	226	95% CI:	[0.9113, 0.9234]
discouraged	450	6,322	AUC-ROC:	0.8459
total	1,644	6,548		

Fig. 6: Performance of our ANN model for predicting development teams' choice to use preferred or discouraged APIs over different code bases. The graphs show the model's performance during the training phase. “Confusion Matrix” and “Evaluation Metrics” show the model's performance on the test set. Our model predicts choices with 92% accuracy.



Confusion Matrix			Evaluation Metrics	
	reference			
prediction	preferred	discouraged	Accuracy:	0.8633
preferred	9,704	1,726	95% CI:	[0.8605, 0.8661]
discouraged	6,431	41,823	AUC-ROC:	0.7879
total	16,135	43,549		

Fig. 7: Performance of our ANN model for predicting development team's choice to use preferred or discouraged APIs in the future from their past development activity. The graphs show the model's performance during the training phase. “Confusion Matrix”, and “Evaluation Metrics” show the model's performance on the test set. Our model predicts future choices with 86% accuracy.

The bottom of Figure 6 shows the trained ANN model's performance on the test set in terms of the evaluation metrics. As shown, our model can predict whether teams will use preferred or discouraged APIs with 92% accuracy, and the 0.8459 AUC-ROC shows this is excellent performance for this prediction task.

An artificial-neural-network (ANN)-based model can predict whether developers will use preferred or discouraged APIs with 92% accuracy.

RQ3: Can development team's past activity, encoded in terms of the correlated factors, predict future standard adherence? The graphs at the top of Figure 7 show the training of the ANN model for 100 epochs. As shown, the loss decreases and the accuracy increases on the training and validation sets with increasing epochs and the convergence is achieved after ~88 epochs. After 100 epochs, the accuracy on the training set was 93.60% and the validation set was 70.80%.

The bottom of Figure 7 shows the trained ANN model's performance on the test set in terms of the evaluation metrics. As shown, the model predicts if developers will use preferred or discouraged APIs with 86% accuracy, and the 0.7879 AUC-ROC indicates the model's performance is acceptable.

For the large code base with a decade of development activity, an ANN-based model can predict if a team will use preferred or discouraged APIs in the future with 86% accuracy based on 7 factors computed from past development activity.

D. Discussion and Threats to Validity

The factors presented in this paper are not an exhaustive list and other factors could influence development teams' compliance. For example, studies [78], [81]–[83] show that factors related to SAT warnings are useful to improve SAT accuracy. However, we do not consider such factors because recent research showed that these factors cause data leakage, leading to misleading results [28]. Further, a factor can encode organization-specific context, and it is important to understand the impact of such factors on the study. For example, instead of using years of experience, we use *YearsOfMSExperience* that measures the developers' work experience at Microsoft and disregards their previous experiences. We made this choice because other companies may not use the Banned API Standard, and so even experienced developers who are new to Microsoft may be a novice when it comes to Banned API Standard. Therefore, we consider such developers to be novices. Although our methodology and factors generalize to other software development scenarios, the results presented for the Banned API Standard detected using sarif-pattern-matcher are observational and rely on the dataset used for our analysis.

The ANN model to predict development team's future adherence to the Banned API Standard from their past behavior performed reasonably well by using only 7 of the 23 correlated factors in a single repository. However, when we used the same set of factors to perform analysis over code bases, the accuracy of the model dropped significantly. This indicates that factors that vary across different teams contribute significantly when predicting adherence over multiple code bases. These results are consistent with a prior study [36] and our observation that different teams at Microsoft had different adherence behaviors.

We address the threat to external validity by ensuring that our evaluation datasets consist of the large and diverse repositories that are representative of real-world software development. We address the threat to internal validity by computing necessary evaluation metrics ("effect size", "95% CI" and "AUC-ROC"), which give us statistical assurance that our results are not influenced merely by the large size of our dataset. Our collected dataset is incomplete, missing some values, particularly about the developers. This is not uncommon in data collected from databases from multiple, real-world, complex systems. We address threats posed by incomplete data by only using the data points for which we have complete data for our prediction modeling, and only using non-missing data points for correlation computations. Our methods of detecting API usages and computing *IsTestCode* and *IsActiveCode* features use a heuristics-based approach; their accuracy may influence our findings. While we use SMOTE, a popular technique to balance the imbalanced training sets to prevent classification bias, our results for predictions show that our models predict discouraged APIs more accurately than the preferred ones. This could be attributed to the SMOTE's performance in creating synthetic data points. We address this threat of classification bias by computing AUC-ROC and confusion matrix to analyze predictions for discouraged and preferred API usages separately.

V. Actionable advice for SAT designers

Our analysis focused on the Banned API Standard and sarif-pattern-matcher, but our methodology (Figure 1) and the influencing factors (Figure 2) are standard and tool agnostic. We next advise SAT designers how to improve SATs.

Prioritizing warnings based on context. SATs can predict which warnings the teams are more likely to address — whether by fixing the warnings or by adding safety checks or taking other risk-mitigation steps — and rank those warnings higher. For example, our analysis shows that prioritizing warnings in production code, actively-under-development code, code being worked on by more developers, and code with higher churn is likely to get the warnings teams address to be seen sooner.

Prioritizing warnings based on prior behavior and improve fix suggestions. SATs can observe teams' behavior on code and extrapolate that behavior to prioritize warnings. For example, our analysis observed that when reusing legacy code, teams were less likely to replace discouraged APIs. If the SAT identifies a warning in legacy code that has been reused elsewhere by other teams, and those teams elected not to replace the APIs, making them as "won't fix," the current team is likely to do the same. The SAT can further make suggestions for fixes similar to prior teams, such as adding additional safety checks, rather than replacing the APIs. A SAT that checks adherence to multiple standards can prioritize the warnings of the standard more often complied to by the team.

Improving warnings content based on developer needs. Our analysis identified that more experienced developers are more likely to address warnings than novice developers. Potentially, SATs can improve by customizing the information displayed with the warning. Novice developers may need to see more context and deeper explanations of why a discouraged API is unsafe, as well as potential solutions. More experienced developers may only need to see the discouraged API use and suggested preferred API.

Modern IDEs can run static analysis with every build (and some proposals even suggest running static and dynamic analyses in the background, continuously [29], [67], [68]). SATs running in this way can use our models in a form of speculative analysis [7], [8], [56] to predict teams' actions and proactively suggest the best coding practices suitable for the given development context. Displaying all warnings in such a continuous manner is likely to overwhelm the developer, but using our predictive models can help focus the developer on the most pertinent warnings that they are likely to address.

VI. Related Work

Several studies have been conducted to identify developer factors that affect code quality. Salamea et al. [69] analyzed two open-source projects to investigate how code quality, measured in terms of technical debt (TD) (number of code smells (e.g., duplicated code) produced per developer), is affected by developer participation, experience, and communication skills. They found that the level of participation (lines of code contributed) of the developers and their experience (number of months active) in the project have a positive correlation with the amount of TD while their communication skills have barely any impact. Alfayez et al. [3] analyzed 38 Apache projects to investigate how developers' frequency of commits, their seniority, and the size of time lapses between their commits relate to code quality. They found that developers' frequency of commits and seniority are negatively correlated with introducing defects and the size of the time lapses between developers' commits is positively correlated with introducing defects in code.

Tufano et al. [76] analyzed five open-source Java projects to identify how commit coherence (i.e., how much it is focused on a specific topic), developers' experience (measured using the metrics that compute developers' familiarity with the files modified by them based on their commits), and the interfering changes performed prior by other developers on the files involved influence the likelihood that a commit induces a fix. They found that fix-inducing commits are less coherent, are produced by more experienced developers, and have a higher number of past interfering changes than commits that did not induce a fix. Li et al. [38] analyzed data of 76 developers in four open-source software projects to understand how developers' bug-introducing commit rates change over time, and its possible dependency on lines of code (LOC). They showed that developers' bug-introducing commit rates tend to include two phases: a first increasing phase and a decreasing phase. Further, larger (in terms of LOC) commits introduce a higher number of software defects. Qui et al. [61] analyzed six open-source projects to investigate how developer quality (rate of non-bug-introducing commits) relates to software evolution. They found that developer quality tends to increase with software evolution, developers with more code contribution are more likely to have higher developer quality, and source code ownership does not have a consistent and significant correlation with developer quality. Rahman et al. [62] analyzed four open-source projects to understand how developers' file ownership, file experience, and overall experience impact code quality. They reported that multiple developers contributing to the same file reduces defective code, developers introduce fewer defects in their own files, and developer general experience (measure in terms of the deltas committed to a repository up to a particular time) has a weak relationship with code quality. Lavallée et at. [36] investigated how organizational factors such as structure and culture impact the working conditions of developers. They found that some software teams tend to prefer quick-and-dirty solutions over time-consuming ones, incurring technical debt due to fear of exceeding their budget. All of these studies consider factors that are related to either developer or code base properties.

Our work extends the state-of-the-art by using factors covering both, developer and code base aspects, along with the properties of code-quality standards.

Due to the variable nature of code quality standards and the onerous manual efforts required for compliance, the industry is becoming more efficient by using automated means of recognizing, verifying, delegating, and monitoring compliance-related tasks [16], [17]. Code quality is affected not only by the developers but also by the process the developers follow. For example, enforcing static analysis checks at commit time can increase compliance [66], and adhering to testing practices can improve code quality [4]. While certain types of tests can be automatically generated, e.g., regression tests via Randoop [58] or EvoSuite [15], most testing for new functionality requires human-written oracles. Recent work has aimed to generate such oracles automatically from comments or natural-language specifications. Swami [52] generates oracles from semi-structured specification and is able to discover defects in code and ambiguities in specifications in mature projects, such as the Rhino and Node.js JavaScript implementations. Toradacu [20] and Jdoctor [6] and @tComment [74] extract oracles from Javadoc comments, with Toradacu and Jdoctor focusing on extracting oracles for exceptional behavior and @tComment on extracting preconditions related to nullness of parameters. C2S [86] captures developers' intent by automatically translating natural language comments in the source code into formal program specifications.

In addition to static analyses that make suggestions for developers for improving code quality, it is possible to improve code quality automatically. Automated program repair aims to automatically repair failing tests by modifying the source code via a variety of methods [37]. For example, genetic algorithms and random search through the space of modifications can often find patches that pass the supplied tests [59], [79]. Unfortunately, these repair mechanisms can often break untested or undertested behavior [54], [60], [70], and while some recent advances have improved the frequency with which automated program repair techniques produce correct patches [1], [30], [53], [84], [87], improving the quality of automatically generated patches remains an open problem.

VII. Future Research Directions

This paper proposes a novel approach to predict circumstances in which development teams are likely to adhere to a quality standard and act on the *true positive* warnings raised by SATs. To accomplish this, our approach detects instances of adherence to and noncompliance with a quality standard, and developer and programming-context factors that correlate with these instances. Our next steps are to use our findings to improve SATs for the Banned API Standard and conduct user studies to evaluate the effects of our improvements in practice. However, this paper is merely a first step towards understanding the relationships between these factors and teams' adherence. While our work potentially allows SATs to detect context-aware situations in which to interpret rule applicability, future research can consider methods for detecting context-aware situations that violate or adhere to code-quality standards undetectable by rules alone. This can extend SATs to detecting violations and compliances of more complex code-quality standards than is possible today.

VIII. Contributions

We have studied the problem of identifying when and why development teams adhere to or deviate from code-quality standards with the aim of improving SATs' utilization. Our large-scale case study at Microsoft has identified the factors that affect the teams' adherence and allowed the creation of models for predicting situations in which teams will choose to deviate from or adhere to the standards. SATs can use these models to prioritize and customize their warnings, improving their utility to the development process.

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References

[1] A. Afzal, M. Motwani, K. T. Stolee, Y. Brun, and C. Le Goues. SOSRepair: Expressive semantic search for real-world program repair. *IEEE Transactions on Software Engineering (TSE)*, 47(10):2162–2181, October 2021.

[2] A. V. Aho, M. S. Lam, R. Sethi, and J. D. Ullman. *Compilers: Principles, Techniques, and Tools (2nd Edition)*. Addison-Wesley Longman Publishing Co., Inc., 2006.

[3] R. Alfayez, P. Behnamghader, K. Srisopha, and B. Boehm. An exploratory study on the influence of developers in technical debt. In *International Conference on Technical Debt*, pages 1–10, 2018.

[4] P. Ammann and J. Offutt. *Introduction to Software Testing*. Cambridge University Press, 1st edition, 2008.

[5] M. Beller, R. Bholanath, S. McIntosh, and A. Zaidman. Analyzing the state of static analysis: A large-scale evaluation in open source software. In *International Conference on Software Analysis, Evolution, and Reengineering (SANER)*, pages 470–481, 2016.

[6] A. Blasi, A. Goffi, K. Kuznetsov, A. Gorla, M. D. Ernst, M. Pezzè, and S. D. Castellanos. Translating code comments to procedure specifications. In *International Symposium on Software Testing and Analysis (ISSTA)*, pages 242–253, 2018.

[7] Y. Brun, R. Holmes, M. D. Ernst, and D. Notkin. Proactive detection of collaboration conflicts. In *Joint Meeting of the European Software Engineering Conference and ACM SIGSOFT Symposium on the Foundations of Software Engineering (ESEC/FSE)*, pages 168–178, September 2011.

[8] Y. Brun, R. Holmes, M. D. Ernst, and D. Notkin. Early detection of collaboration conflicts and risks. *IEEE Transactions on Software Engineering (TSE)*, 39(10):1358–1375, October 2013.

[9] C. Calcagno and D. Distefano. Infer: An automatic program verifier for memory safety of C programs. In *NASA Formal Methods Symposium*, pages 459–465, 2011.

[10] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

[11] M. Copeland. Kusto query language and threat hunting. In *Cloud Defense Strategies with Azure Sentinel*, pages 185–211. Springer, 2021.

[12] W. A. Dahl, L. Erdodi, and F. M. Zennaro. Stack-based buffer overflow detection using recurrent neural networks. *CoRR*, abs/2012.15116, 2020.

[13] E. Dauber, A. Caliskan, R. Harang, and R. Greenstadt. Git blame who? Stylistic authorship attribution of small, incomplete source code fragments. In *Poster Track at the International Conference on Software Engineering*, pages 356–357, 2018.

[14] L. Flynn, W. Snavely, D. Svoboda, N. VanHoudnos, R. Qin, J. Burns, D. Zubrow, R. Stoddard, and G. Marce-Santurio. Prioritizing alerts from multiple static analysis tools, using classification models. In *International Workshop on Software Qualities and their Dependencies (SQUADE)*, pages 13–20, 2018.

[15] G. Fraser and A. Zeller. Mutation-driven generation of unit tests and oracles. In *International Symposium on Software Testing and Analysis (ISSTA)*, pages 147–158, 2010.

[16] S. Ghaisas, M. Motwani, and P. R. Anish. Detecting system use cases and validations from documents. In *International Conference on Automated Software Engineering (ASE)*, pages 568–573, 2013.

[17] S. Ghaisas, M. Motwani, B. Balasubramaniam, A. Gajendragadkar, R. Kelkar, and H. Vin. Towards automating the security compliance value chain. In *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*, pages 1014–1017, 2015.

[18] G. E. Gignac and E. T. Szodorai. Effect size guidelines for individual differences researchers. *Personality and Individual Differences*, 102:74–78, 2016.

[19] G. V. Glass. Note on rank biserial correlation. *Educational and Psychological Measurement*, 26(3):623–631, 1966.

[20] A. Goffi, A. Gorla, M. D. Ernst, and M. Pezzè. Automatic generation of oracles for exceptional behaviors. In *International Symposium on Software Testing and Analysis (ISSTA)*, pages 213–224, July 2016.

[21] A. Gosain and G. Sharma. Static analysis: A survey of techniques and tools. In *Intelligent Computing and Applications*, pages 581–591. Springer India, 2015.

[22] A. Habib and M. Pradel. How many of all bugs do we find? a study of static bug detectors. In *International Conference on Automated Software Engineering (ASE)*, pages 317–328, 2018.

[23] Q. Hanam, L. Tan, R. Holmes, and P. Lam. Finding patterns in static analysis alerts: Improving actionable alert ranking. In *Mining Software Repositories (MSR)*, pages 152–161, 2014.

[24] S. Heckman and L. Williams. On establishing a benchmark for evaluating static analysis alert prioritization and classification techniques. In *International Symposium on Empirical Software Engineering and Measurement (ESEM)*, pages 41–50, 2008.

[25] M. Howard and S. Lipner. *The security development lifecycle*, volume 8. Microsoft Press Redmond, 2006.

[26] R. Huuck, A. Fehnker, S. Seefried, and J. Brauer. Goanna: Syntactic software model checking. In *International Symposium on Automated Technology for Verification and Analysis*, pages 216–221, 2008.

[27] N. Imtiaz, B. Murphy, and L. Williams. How do developers act on static analysis alerts? An empirical study of coverity usage. In *International Symposium on Software Reliability Engineering (ISSRE)*, pages 323–333, 2019.

[28] H. J. Kang, K. L. Aw, and D. Lo. Detecting false alarms from automatic static analysis tools: How far are we? In *International Conference on Software Engineering (ICSE)*, 2022.

[29] H. Katzan, Jr. Batch, conversational, and incremental compilers. In *Spring Joint Computer Conference*, pages 47–56, 1969.

[30] Y. Ke, K. T. Stolee, C. Le Goues, and Y. Brun. Repairing programs with semantic code search. In *International Conference on Automated Software Engineering (ASE)*, pages 295–306, November 2015.

[31] S. Kim and M. D. Ernst. Prioritizing warning categories by analyzing software history. In *Mining Software Repositories (MSR)*, 2007.

[32] U. Koc, P. Saadatpanah, J. S. Foster, and A. A. Porter. Learning a classifier for false positive error reports emitted by static code analysis tools. In *International Workshop on Machine Learning and Programming Languages (MAPL)*, page 35–42, 2017.

[33] U. Koc, S. Wei, J. S. Foster, M. Carpuat, and A. A. Porter. An empirical assessment of machine learning approaches for triaging reports of a java static analysis tool. In *Conference on Software Testing, Validation and Verification (ICST)*, pages 288–299, 2019.

[34] T. Kremenek, K. Ashcraft, J. Yang, and D. Engler. Correlation exploitation in error ranking. In *International Symposium on Foundations of Software Engineering (FSE)*, pages 83–93, 2004.

[35] T. Kremenek and D. Engler. Z-ranking: Using statistical analysis to counter the impact of static analysis approximations. In *International Static Analysis Symposium (SAS)*, pages 295–315, 2003.

[36] M. Lavallée and P. N. Robillard. Why good developers write bad code: An observational case study of the impacts of organizational factors on software quality. In *International Conference on Software Engineering (ICSE)*, pages 677–687, 2015.

[37] C. Le Goues, M. Pradel, and A. Roychoudhury. Automated program repair. *Communications of the ACM*, 62(12):56–65, Nov. 2019.

[38] Y. Li, D. Li, F. Huang, S.-Y. Lee, and J. Ai. An exploratory analysis on software developers' bug-introducing tendency over time. In *IEEE International Conference on Software Analysis, Testing and Evolution (SATE)*, pages 12–17, 2016.

[39] G. Liang, L. Wu, Q. Wu, Q. Wang, T. Xie, and H. Mei. Automatic construction of an effective training set for prioritizing static analysis warnings. In *International Conference on Automated Software Engineering (ASE)*, page 93–102, 2010.

[40] K. Liu, D. Kim, T. F. Bissyandé, S. Yoo, and Y. Le Traon. Mining fix patterns for findbugs violations. *IEEE Transactions on Software Engineering (TSE)*, 47(1):165–188, 2021.

[41] J. N. Mandrekar. Receiver operating characteristic curve in diagnostic test assessment. *Journal of Thoracic Oncology*, 5(9):1315–1316, 2010.

[42] T. Marchant-Shapiro. Chi-square and cramer's v: what do you expect. *Statistics for political analysis: Understanding the numbers*, pages 245–272, 2015.

[43] D. Marcilio, R. Bonifácio, E. Monteiro, E. Canedo, W. Luz, and G. Pinto. Are static analysis violations really fixed? A closer look at realistic usage of SonarQube. In *International Conference on Program Comprehension (ICPC)*, pages 209–219, 2019.

[44] D. Marcilio, C. A. Furia, R. Bonifácio, and G. Pinto. Automatically generating fix suggestions in response to static code analysis warnings. In *International Working Conference on Source Code Analysis and Manipulation (SCAM)*, pages 34–44. IEEE, 2019.

[45] D. Marcilio, C. A. Furia, R. Bonifácio, and G. Pinto. Spongebugs: Automatically generating fix suggestions in response to static code analysis warnings. *Journal of Systems and Software*, 168:110671, 2020.

[46] M. L. McHugh. The chi-square test of independence. *Biochemia medica: Biochemia medica*, 23(2):143–149, 2013.

[47] P. E. McKnight and J. Najab. Mann-whitney U test. *The Corsini encyclopedia of psychology*, 2010.

[48] Microsoft. Microsoft security development lifecycle. https://www.microsoft.com/en-us/securityengineering/sdl/, 2021.

[49] Microsoft. Practice #9 - perform static analysis security testing (SAST). https://www.microsoft.com/en-us/securityengineering/sdl/practices/\#practice9, 2021.

[50] Microsoft. sarif-pattern-matcher. https://github.com/microsoft/sarif-pattern-matcher, 2021.

[51] A. Miné, L. Mauborgne, X. Rival, J. Feret, P. Cousot, D. Kästner, S. Wilhelm, and C. Ferdinand. Taking static analysis to the next level: proving the absence of run-time errors and data races with astrée. In *European Congress on Embedded Real Time Software and Systems (ERTS)*, 2016.

[52] M. Motwani and Y. Brun. Automatically generating precise oracles from structured natural language specifications. In *International Conference on Software Engineering (ICSE)*, pages 188–199, May 2019.

[53] M. Motwani and Y. Brun. Better automatic program repair by using bug reports and tests together. In *International Conference on Software Engineering (ICSE)*, May 2023.

[54] M. Motwani, M. Soto, Y. Brun, R. Just, and C. Le Goues. Quality of automated program repair on real-world defects. *IEEE Transactions on Software Engineering (TSE)*, 48(2):637–661, February 2022.

[55] T. Muske and A. Serebrenik. Survey of approaches for handling static analysis alarms. In *International Working Conference on Source Code Analysis and Manipulation (SCAM)*, pages 157–166, 2016.

[56] K. Muşlu, Y. Brun, R. Holmes, M. D. Ernst, and D. Notkin. Speculative analysis of integrated development environment recommendations. In *Conference on Object-Oriented Programming, Systems, Languages, and Applications (OOPSLA)*, pages 669–682, October 2012.

[57] R. Newson. Parameters behind "nonparametric" statistics: Kendall's tau, somers' d and median differences. *The Stata Journal*, 2(1):45–64, 2002.

[58] C. Pacheco and M. D. Ernst. Randoop: Feedback-directed random testing for Java. In *Conference on Object-oriented Programming Systems and Applications (OOPSLA)*, pages 815–816, 2007.

[59] Y. Qi, X. Mao, and Y. Lei. Efficient automated program repair through fault-recorded testing prioritization. In *International Conference on Software Maintenance (ICSM)*, pages 180–189, Sept. 2013.

[60] Z. Qi, F. Long, S. Achour, and M. Rinard. An analysis of patch plausibility and correctness for generate-and-validate patch generation systems. In *International Symposium on Software Testing and Analysis (ISSTA)*, pages 24–36, 2015.

[61] Y. Qiu, W. Zhang, W. Zou, J. Liu, and Q. Liu. An empirical study of developer quality. In *International Conference on Software Quality, Reliability, and Security Companion (QRS-C)*, pages 202–209, 2015.

[62] F. Rahman and P. Devanbu. Ownership, experience and defects: A fine-grained study of authorship. In *International Conference on Software Engineering (ICSE)*, pages 491–500, 2011.

[63] T. Rains. Microsoft's Free Security Tools – banned.h. https://www.microsoft.com/en-us/security/blog/2012/08/30/microsofts-free-security-tools-banned-h/, 2012.

[64] J. R. Ruthruff, J. Penix, J. D. Morgenthaler, S. Elbaum, and G. Rothermel. Predicting accurate and actionable static analysis warnings: An experimental approach. In *International Conference on Software Engineering (ICSE)*, page 341–350, 2008.

[65] V. Sachidananda, S. Bhairav, and Y. Elovici. OVER: Overhauling vulnerability detection for IoT through an adaptable and automated static analysis framework. In *Symposium on Applied Computing*, pages 729–738, 2020.

[66] C. Sadowski, E. Aftandilian, A. Eagle, L. Miller-Cushon, and C. Jaspan. Lessons from building static analysis tools at google. *Communications of the ACM*, 61(4):58–66, 2018.

[67] D. Saff and M. D. Ernst. Reducing wasted development time via continuous testing. In *International Symposium on Software Reliability Engineering (ISSRE)*, pages 281–292, November 2003.

[68] D. Saff and M. D. Ernst. An experimental evaluation of continuous testing during development. In *International Symposium on Software Testing and Analysis (ISSTA)*, pages 76–85, July 2004.

[69] M. J. Salamea and C. Farré. Influence of developer factors on code quality: A data study. In *International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, pages 120–125, 2019.

[70] E. K. Smith, E. Barr, C. Le Goues, and Y. Brun. Is the cure worse than the disease? overfitting in automated program repair. In *Joint Meeting of the European Software Engineering Conference and ACM SIGSOFT Symposium on the Foundations of Software Engineering (ESEC/FSE)*, pages 532–543, September 2015.

[71] J. Smith, B. Johnson, E. Murphy-Hill, B. Chu, and H. R. Lipford. How developers diagnose potential security vulnerabilities with a static analysis tool. *IEEE Transactions on Software Engineering*, 45(9):877–897, 2018.

[72] M. Stagg. This Microsoft Windows RCE vulnerability gives an attacker complete control. https://www.synack.com/blog/this-microsoft-windows-rce-vulnerability-gives-an-attacker-complete-control/, 2021.

[73] D. Svozil, V. Kvasnicka, and J. Pospichal. Introduction to multi-layer feed-forward neural networks. *Chemometrics and intelligent laboratory systems*, 39(1):43–62, 1997.

[74] S. H. Tan, D. Marinov, L. Tan, and G. T. Leavens. @tComment: Testing Javadoc comments to detect comment-code inconsistencies. In *International Conference on Software Testing, Verification, and Validation (ICST)*, pages 260–269, 2012.

[75] D. A. Tomassi. Bugs in the wild: Examining the effectiveness of static analyzers at finding real-world bugs. In *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*, pages 980–982, 2018.

[76] M. Tufano, G. Bavota, D. Poshyvanyk, M. Di Penta, R. Oliveto, and A. De Lucia. An empirical study on developer-related factors characterizing fix-inducing commits. *Journal of Software: Evolution and Process*, 29(1):e1797, 2017.

[77] C. Vassallo, S. Panichella, F. Palomba, S. Proksch, H. C. Gall, and A. Zaidman. How developers engage with static analysis tools in different contexts. *Empirical Software Engineering*, 25(2):1419–1457, 2020.

[78] J. Wang, S. Wang, and Q. Wang. Is there a "golden" feature set for static warning identification? An experimental evaluation. In *International Symposium on Empirical Software Engineering and Measurement (ESEM)*, 2018.

[79] W. Weimer, T. Nguyen, C. Le Goues, and S. Forrest. Automatically finding patches using genetic programming. In *International Conference on Software Engineering (ICSE)*, pages 364–374, 2009.

[80] C. Williams and J. Hollingsworth. Automatic mining of source code repositories to improve bug finding techniques. *IEEE Transactions on Software Engineering*, 31(6):466–480, 2005.

[81] X. Yang, J. Chen, R. Yedida, Z. Yu, and T. Menzies. Learning to recognize actionable static code warnings (is intrinsically easy). *Empirical Software Engineering*, 26(3):1–24, 2021.

[82] X. Yang and T. Menzies. Documenting evidence of a reproduction of 'is there a "golden" feature set for static warning identification? — an experimental evaluation'. In *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*, page 1603, 2021.

[83] X. Yang, Z. Yu, J. Wang, and T. Menzies. Understanding static code warnings: An incremental ai approach. *Expert Systems with Applications*, 167:114134, 2021.

[84] H. Ye, M. Martinez, and M. Monperrus. Neural program repair with execution-based backpropagation. In *International Conference on Software Engineering (ICSE)*, page 1506–1518, 2022.

[85] U. Yüksel and H. Sözer. Automated classification of static code analysis alerts: A case study. In *International Conference on Software Maintenance (ICSM)*, pages 532–535, 2013.

[86] J. Zhai, Y. Shi, M. Pan, G. Zhou, Y. Liu, C. Fang, S. Ma, L. Tan, and X. Zhang. C2S: Translating natural language comments to formal program specifications. In *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*, page 25–37, 2020.

[87] Q. Zhu, Z. Sun, Y. an Xiao, W. Zhang, K. Yuan, Y. Xiong, and L. Zhang. A syntax-guided edit decoder for neural program repair. In *Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*, page 341–353, 2021.