The Scent of Test Effectiveness: Can Scriptless Testing Reveal Code Smells?

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Abstract: This paper presents an industrial experience applying random scriptless GUI testing to the Yoho web application developed by Marviq. The study was motivated by several key challenges faced by the company, including the need to optimise testing resources, explore how random testing can complement manual testing, and investigate new coverage metrics, such as “code smell coverage”, to assess software quality and maintainability. We conducted an experiment to explore the impact of the number and length of random GUI test sequences on traditional adequacy metrics, the complementarity of random with manual testing, and the relationship between code smell coverage and traditional code coverage. Using Testar for scriptless testing and SonarQube code smell identification, results show that longer random test sequences yielded better test adequacy metrics and increased code smell coverage. In addition, random testing offers promising efficiency in test coverage and detects unique smells that manual testing might overlook. Additionally, including code smell coverage provides valuable insights into long-term code maintainability, revealing gaps that traditional metrics may not capture. These findings highlight the benefits of combining functional testing with metrics assessing code quality, particularly in resource-constrained environments.

1 INTRODUCTION

The increasing reliance on complex web applications demands robust software testing practices to prevent bugs that could cause user dissatisfaction, data breaches, and reputational harm (Bons et al., 2023). For companies, testing at the Graphical User Interface (GUI) level is essential, providing insights into the customer experience (Rodríguez-Valdes et al., 2021). However, manually executing GUI tests is resource-intensive and error-prone, particularly in regression testing, prompting a shift toward automation.

Automated GUI testing approaches fall into two categories: scripted and scriptless. *Scripted testing* utilises predefined scripts based on specific use cases, requiring extensive maintenance when the GUI changes (Alégroth et al., 2016). In contrast, *scriptless testing* dynamically generates test sequences by exploring the GUI in real-time, reducing maintenance needs but introducing challenges in action selection and automation of oracles (Vos et al., 2021).

Synthesis of 5 case-based studies (Vos et al., 2021) using an architectural analogy (Wieringa and Daneva, 2015) has demonstrated that scriptless GUI testing complements traditional scripted testing techniques. Despite these advantages, industrial adoption remains limited (Rodríguez-Valdes et al., 2021).

In collaboration with the private company Marviq and under the European IVVES project, we identified several critical needs influencing the adoption of scriptless testing in industrial settings: (1) optimisation of test session length to balance coverage and time efficiency; (2) evaluation of random GUI testing as a complement to existing manual testing processes; (3) introduction of code smell coverage to ad-

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dress maintainability and technical debt; (4) assessment of correlations between code smell coverage and traditional coverage metrics to identify testing gaps.

Addressing these needs requires considering both the breadth of code tested and its quality. Traditional metrics (e.g., line, branch, and complexity coverage) are widely used but have limitations in capturing the quality of testing (Inozemtseva and Holmes, 2014)(Madeyski, 2010). High code coverage may not guarantee thorough testing or the detection of subtle defects, leaving critical quality aspects overlooked.

This paper explores code smells as a metric for evaluating traditional coverage metrics within the context of an industrial web application. Code smells indicate potential maintainability issues and hidden bugs (Pereira dos Reis et al., 2022). Covering these smells during testing can reflect the ability of the testing tool to detect deeper quality issues. While static analysis identifies potential smells, dynamic testing ensures these smells are encountered during real application use, increasing confidence in addressing areas that may contribute to defects and boosting confidence in overall software quality.

Our study uses SonarQube[1] for code smell detection and the Testar tool (Vos et al., 2021) for scriptless GUI testing to assess the impact of test sequence length on coverage and investigates correlations between code smells and traditional coverage metrics. Additionally, we evaluate the complementarity of scriptless testing with Marviq's manual testing process. This collaboration brings significant relevance, as it adds a real-world and practical component to our study and another industrial validation of scriptless GUI testing needed for case study generalisation through architectural analogy (Wieringa and Daneva, 2015). The contribution of this paper is threefold:

1. We conduct an empirical study to analyse the influence of test sequence length on traditional coverage metrics.
2. We propose using known code smells in an industrial application to evaluate the effectiveness of traditional coverage metrics in exploring a system.
3. We compare random scriptless testing with Marviq's manual testing process to demonstrate their complementarity and the potential of scriptless testing.

This research offers insights for software testing professionals and researchers interested in expanding traditional coverage metrics to include maintainability aspects. By integrating code smell detection, we contribute to developing testing techniques that address both functionality and software quality. Moreover, new research directions open up exploring the relationship between GUI testing and code smells.

The paper is structured as follows. Section 2 presents the state of the art in random scriptless GUI testing, adequacy metrics and code smell analysis. Section 3 describes the industrial context. Section 4 describes the experiments, and Section 5 shows the results and answers to the research questions. Section 6 discusses Marviq's perspective of the findings, while Section 7 addresses validity threats. Finally, section 8 concludes the work and summarises future research.

[1]https://www.sonarsource.com/products/sonarqube/

2 RELATED WORK

Random Scriptless GUI Testing. GUI testing is essential for ensuring the reliability and functionality of modern software. One of the key techniques in this domain is *random scriptless GUI testing*, where agents autonomously interact with the GUI by generating and executing random user interactions. While effective at identifying faults, its success largely depends on the configuration of randomisation parameters. Recent studies show that test outcomes are significantly influenced by sequence length, state abstraction, and stopping criteria (Tramontana et al., 2019) (Amalfitano et al., 2017).

Improving the effectiveness of random GUI testing requires adapting the strategy to overcome specific challenges presented by GUI components, such as blocking GUIs that need specific user interactions to be unlocked. Recent work has introduced novel techniques to enhance the ability of random agents to navigate and test complex interfaces, thereby improving testing adequacy (Amalfitano et al., 2019).

Furthermore, a body of research compares random testing with manual testing approaches, highlighting their complementarity. Manual testing can cover parts of the code that random testing might miss, while random approaches uncover unexpected interactions and pathways that manual testers may overlook. This complementarity suggests that a hybrid strategy, combining both methods, could enhance coverage and fault detection (Martino et al., 2024) (Jansen et al., 2022).

Test Adequacy Metrics. Code coverage is widely used to evaluate testing quality by linking it to test effectiveness (Hemmati, 2015), (Kochhar et al., 2015), (Gligoric et al., 2013), (Pradhan et al., 2019). While coverage metrics act as surrogate measures of testing thoroughness, studies suggest that coverage criteria alone are a poor indicator of test quality (Staats et al., 2012), highlighting the need for approaches beyond code coverage (Tengeri et al., 2015).

A comprehensive comparison of Android GUI testing tools was conducted using line of executable code coverage (Choudhary et al., 2015). Similarly, various automated Android testing tools were compared based on method and activity coverage, and fault detection (Wang et al., 2018). Branch coverage was the primary metric in a study comparing random testing and search-based test data generation for web applications(Alshahwan and Harman, 2011). Instruction and branch were assessed for Java applications to evaluate effectiveness (van der Brugge et al., 2021). Likewise, line and statement coverage were used to propose a framework to evaluate the effectiveness of Android GUI testing tools (Amalfitano et al., 2017). Recently, the effectiveness of a reinforcement learning testing approach for Android was examined using instruction, branch, line and method coverage in(Collins et al., 2021). An image-based GUI testing approach was also empirically evaluated for Android and Web applications using line coverage and branch coverage (Yu et al., 2024).

Code coverage metrics have been noted to overlook problematic interactions between the GUI user events and the application, prompting the need for new perspectives in GUI testing coverage criteria (Memon, 2002). Subsequently, an empirical evaluation analysed the impact of test suite size on fault detection, showing that larger test suites identify more seeded faults in toy projects (Memon and Xie, 2005). This conclusion aligns with the idea that higher coverage indicates deeper system exploration, improving fault detection. However, it raises the question of which traditional coverage metrics are the best indicators of test quality in real-world projects.

Code Smells. Indicators of design flaws or issues in source code, known as code smells (Fowler, 2018), can reflect the ability of the testing tool to detect deeper quality issues when identified during testing. Existing research on code smells primarily focus on prioritization (Sae-Lim et al., 2018), (Fontana et al., 2015a), (Codabux and Williams, 2016), filtration (Fontana et al., 2015b), and the code smells-faults correlation (Rahman et al., 2023), (Olbrich et al., 2010), (Gondra, 2008).

The relationship between code smells and test coverage has been studied (Spadini et al., 2018), showing that classes with smells often have lower test coverage. In (Bavota et al., 2015), an exploration of the link between quality metrics, the presence of code smells, and refactoring activities reveals that only 7% of the refactoring on smelly classes actually removed

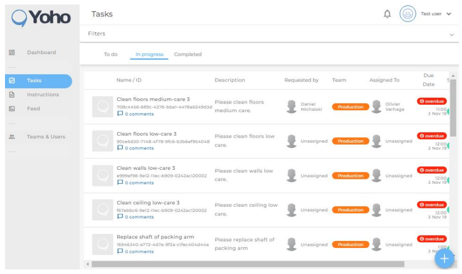


Figure 1: Excerpt of the Yoho SUT.

Table 1: Overview of the size of the Yoho SUT.

Metrics	Yoho	Metrics	Yoho
Java Classes	569	Methods	3033
Java Classes (incl. interfaces)	709	SLOC	25099
Branches	1622	LLOC	9059
Cyclomatic Complexity	3856	Instructions	37180

the smells, suggesting developers tend to mitigate issues rather than completely removing the smell.

While these studies have made important steps in linking code smells to test quality, a gap remains in assessing how traditional coverage metrics relate to code smells. To the best of our knowledge, this study is the first to assess the predictive power of traditional coverage metrics for testing quality using known code smells in an industrial application. We use Testar, an open-source scriptless GUI testing tool with proven industrial value (Bauersfeld et al., 2014), (Pastor Ricós et al., 2020), (Chahim et al., 2018), (Pastor Ricós et al., 2024). This work provides a deeper analysis of the industrial application of scriptless testing presented in (Vos et al., 2021), contributing to the generalisation of the findings using an architectural analogy from (Wieringa and Daneva, 2015).

3 INDUSTRIAL CASE

Marviq[2] is a software development company offering Team as a Service, Software Development as a Service and IoT development, with a focus on integrating skilled professionals into client teams and managing entire development projects. Marviq is a small company with 35 professionals working with agile practices on typically eight concurrent development projects while serving 25 clients.

As these projects are tailored to client needs, Marviq applies a tailor-made Quality Assurance (QA) process. However, QA for small companies faces several challenges, such as unclear requirements, the illusion that the prototype is the final product, mismatches between existing software and new business processes, and insufficient time for testing (Hossain,

[2]https://www.marviq.com/

2018), (Vargas et al., 2021).

This research uses Yoho, a digital solution developed by Marviq to enhance operations and communications in industrial environments. Yoho offers features such as alert and notification management, task handling, work instructions, and enhanced communication tools (see Figure 1). Yoho is a software as a service (SaaS) platform with the typical web application functionality.

At its core, Yoho has been designed with highly configurable options and a role-based access mechanism to support future requirements and customer-specific demands. The design includes interaction units tailored by roles, which provokes that while executing tests, a specific role and customer would result in a relatively low percentage of code coverage as not all functionality would be revealed for this user.

Table 1 presents an overview of the size of Yoho. As can be observed, the metrics presented are representative of a real-world application. Additionally, this SUT exposes relevant challenges, such as the dynamism of modern web applications (i.e., dynamic identifiers for the GUI widgets).

Marviq currently uses SonarQube to identify code smells in the Yoho application, providing a rich basis to evaluate the effectiveness of different coverage metrics in testing problematic code areas.

Nevertheless, the company faces several challenges in ensuring effective software testing while managing limited resources. To address these challenges, Marviq identified the need to explore random and manual testing and new coverage metrics to enhance testing efficiency and code quality. The specific needs driving this study are outlined below.

The Need to Conduct Random Testing with Different Session Lengths *(Need 1)*: To *optimise testing resources*, the company aims to ensure an effective and efficient process. Limited testing resources make finding the optimal session length that balances *coverage* and *time* critical. Short testing sessions risk missing critical issues, while longer ones may be inefficient. By experimenting with various session lengths, the goal is to *identify the best trade-off* between test coverage and resource use, which is especially important in Agile environments with *rapid development cycles*, where testing must adapt quickly to tight time frames.

The Need for a New Coverage Metric: Code Smell Coverage *(Need 2)*: The company aims to ensure not only functional correctness but also long-term *high code quality* and maintainability. Traditional metrics like code or method coverage focus on functionality, but *fail to capture* maintainability and readability aspects of the codebase. Introducing *code smell coverage* addresses the need to track *potential technical debt* that could accumulate unnoticed. This metric ensures that even with high functional coverage, the code remains maintainable and scalable, reducing risks of future issues as the software evolves.

The Need to Assess Correlations between Code Smell Coverage and Traditional Metrics *(Need 3)*: The company seeks to determine if traditional metrics like code and method coverage reflect *overall code quality*, as high coverage does not guarantee well-structured or maintainable code. Examining correlations between *code smell coverage* and traditional metrics can *identify gaps* in the testing process. Low correlation would suggest traditional metrics may overlook maintainability concerns. This insight can help the company *develop a more holistic testing approach* that ensures both functionality and code quality.

The Need to Compare Random Testing with Manual Testing *(Need 4)*: With limited resources for manual testing, Marviq seeks to evaluate if *random testing can complement* the existing manual testing processes. Manual testing is labour-intensive and expensive, prompting the need for a solution that can *reduce time and cost* associated with it. Comparing the two approaches will help determine if random testing can detect bugs more efficiently or identify different types of issues that manual testers may miss. The ultimate goal is to *enhance test coverage* while reducing the burden on manual testers, allowing them to focus on more critical or complex scenarios.

4 EXPERIMENT DESIGN

We conducted an experiment to explore the application of random testing on an industrial web application to address the needs discussed in Section 3. Specifically, the study focuses on optimising testing resources, assessing random testing's complementarity to manual testing, and introducing innovative metrics like 'code smell coverage' to monitor code quality and maintainability. We formulated the following three research questions and their rationales to achieve this goal.

RQ1: How do the number and length of random scriptless GUI testing sequences impact the coverage of testing adequacy metrics?

Rationale: This question investigates ***Need 1*** by exploring how variations in session length affect test coverage. The aim is to identify the optimal balance

between thoroughness and resource efficiency in Agile environments with tight testing cycles.
RQ2: How do traditional coverage metrics (e.g., code and method coverage) relate to code smell coverage?
Rationale: This question addresses ***Need 2 and Need 3*** by examining the relationship between traditional and new metrics like code smell coverage. It seeks to evaluate how well traditional metrics reflect overall code quality and to uncover gaps that may require complementary approaches.
RQ3: How can random testing complement or reduce the reliance on manual approaches?
Rationale: This question tackles ***Need 4***, assessing whether random testing can enhance or replace manual testing. The goal is to improve test coverage while reducing the burden on manual testing resources.

The experiment was designed following the guidelines proposed by (Wohlin et al., 2012). Moreover, we follow a methodological framework (Vos et al., 2012) specifically designed to evaluate testing tools in order to encourage future secondary studies.

4.1 Variables

To address the research questions, we define the independent and dependent variables as follows:

4.1.1 Independent Variables

The independent variables refer to the parameters we used to configure the random scriptless GUI testing tool. These variables include:

- **Number of Random Testing Sequences:** the total number of random test sequences executed.
- **Number of GUI Actions per Sequence:** the number of actions executed within each test sequence.
- **Time Delay Between Actions:** the time interval (in seconds) between two consecutive actions.
- **Action Duration:** the time (in seconds) taken for each GUI action to complete.
- **State Abstraction:** defined by the properties of the widgets used to represent the state of the SUT. A *concrete state* encompasses all widgets and their properties, capturing the SUT's precise status, which can lead to a state explosion. In contrast, an *abstract state* is a high-level representation, focusing on a relevant subset of properties.
- **Initial Sequence Needed:** for example, to pass a login screen.
- **Form Filling Enabled:** to fill detected forms with meaningful data.

Additionally, the parameters for detecting code smells are treated as independent variables.

4.1.2 Dependent Variables

To answer the research questions, we measured traditional coverage metrics, such as Line Coverage (LC), Instruction Coverage (IC), Branch Coverage (BC), Complexity Coverage (CoC), Method Coverage (MC), and Class Coverage (ClC). In addition, we defined the following variables to analyse coverage within the state models and to quantify code smells:

- **Abstract State Coverage (AbSC):** The number of abstract states covered in the state model.
- **Abstract Transition Coverage (AbTC):** The number of transitions covered in the abstract state model.
- **Concrete State Coverage (CoSC):** The number of concrete states covered in the concrete state model.
- **Concrete Transition Coverage (CoTC):** The number of transitions covered in the concrete state model.
- **Code Smell Coverage (CSC):** The number of unique code smells encountered. A code smell is considered "covered" when the Java method containing it is executed at least once during testing.
- **Code Smell Occurrences (CSO):** The total number of code smell instances covered during testing, including multiple occurrences of the same smell.

4.2 Experimental Setting

To carry out the experiment, we configured Testar and the SonarQube static analysis platform to evaluate test coverage and code quality metrics effectively.

4.2.1 Testar Configuration

Several key configurations were implemented to optimise the testing of Yoho using Testar. First, we specified the SUT by defining Yoho's URL and establishing the necessary login procedures. This ensured that Testar could consistently access and interact with the application. To focus on exploring the SUT, we applied the blocking principle (Wohlin et al., 2012), turning off Testar's oracles to prevent interruptions.

Testar was configured to use attributes like name, ID, control type, and text content for widget identification. When clickable elements were defined by CSS classes rather than standard attributes, we manually configured clickability to ensure accurate testing. State abstraction (*SA*) consisted of WebWidgetId, WebWidgetName, WebWidgetTextContent and WidgetControlType. The action abstraction followed Testar's default configuration. Specific actions, such as logging out or file uploads, were excluded to keep interactions within the test scope.

At the start of each test run, a mandatory login sequence was executed using consistent credentials to ensure a uniform starting point. Preliminary trials optimised time parameters, setting the action duration to 0.5 seconds and the delay between actions to 0.8 seconds, balancing efficiency and thoroughness.

A BTrace[3] server was integrated alongside Testar to enable real-time instrumentation of Java methods without modifying the source code or interrupting the normal execution of the application. Operating in a separate environment, BTrace intercepted and logged method calls triggered by GUI actions. Details like method and class name, timestamp, and relevant parameters were collected to measure variables such as CSC and CSO, as described in Section 4.1.

4.2.2 SonarQube Configuration

SonarQube (Campbell and Papapetrou, 2013) was used to perform static analysis of the Yoho codebase, identifying code smells and other violations. SonarQube classifies violations by severity: Blocker, Critical, Major, Minor, or Info. In our analysis, SonarQube detected 173 code smell instances, categorised as shown in table 2 using Fowler's (Fowler, 2018) original classification of code smells and a more recent system (Jerzyk and Madeyski, 2023).

Table 2: Code Smell Classification and Severity.

Code Smell	Type	Critical	Major	Minor
Bloaters (26)	Data Clumps	1	0	0
	Long Parameter List	0	11	0
	Primitive Obsession	1	11	2
Couplers (11)	Indecent Exposure	0	11	0
Dispensables (29)	Comments	12	3	0
	Dead Code	0	8	0
	Lazy Class	0	0	1
	Speculative Generality	0	4	1
Lex. Abusers (3)	Inconsistent Naming	0	0	3
Obfuscators (8)	Clever Code	0	1	3
	Inconsistent Style	0	0	4
Object-Orientation Abusers (95)	Conditional Complexity	0	70	0
	Refused Bequest	0	3	20
	Switch Statements	0	0	1
	Temporary Field	0	1	0
Security (1)	Vulnerability	1	0	0
Total (173)		15	123	35
Total excl. comments and dead code (150)		3	112	35

Most detected code smells were categorised as Object-Orientation Abusers. Conditional Complexity was the most frequent, suggesting a need for better adherence to object-oriented design patterns in the Yoho codebase. Although only one security-related issue was found, it was classified as Critical. This analysis provided valuable insights, allowing us to assess the prevalence and severity of code smells in relation to the executed test sequences. Furthermore, code smells in comments and dead code were excluded from the study, as they are not executable, to ensure accurate coverage analysis and responses to the research questions.

4.3 Experimental Procedure

We designed our experiment using three test process configurations, each consisting of 10,000 actions: TP100, TP500 and TP1000. Table 3 shows the details of these configurations. Moreover, the best configuration (TP500, as identified in the answer to RQ1 in Section 5.1) was enhanced with Testar's advanced *form filling* feature to conduct the comparison with manual testing for RQ3. Table 3 also shows the details for this configuration (TP500Forms).

Table 3: Test Process Configurations.

Variable	TP100	TP500	TP1000	TP500Forms
Test sequences	100	20	10	20
Actions per sequence	100	500	1000	500
Time delay (s)	0.8	0.8	0.8	0.8
Action duration (s)	0.5	0.5	0.5	0.5
State abstraction	*SA*	*SA*	*SA*	*SA*
Login sequence	yes	yes	yes	yes
Form filling	no	no	no	yes

Testar's *form filling* feature automatically populates forms with data. As the scriptless tool randomly navigates through the states of the SUT, it detects forms automatically. Upon identifying a form, Testar generates an XML file with each key representing an editable widget within the form, and the corresponding value is an auto-generated input. The following is an example of an automatically generated XML:

```
<form><data>
 <description>RandomText1</description>
 <email>email1@example.com</email>
 <weight>50</weight></data>
 <data>
 <email>email2@example.com</email>
 <weight>50</weight></data>
</form>
```

The generated input data type depends on the widget type (e.g., random text for text fields or valid email addresses for email fields). Each XML file can define multiple weighted input sets for a form, allowing customisation to test varied data combinations. During Testar's configuration, 23 forms with up to six fields were automatically identified within the SUT. Two input profiles were created per form—one with baseline values and another with varied alternatives—requiring one working day (8 hours) to edit and test the 23 XML files. With this functionality in

[3]https://github.com/btraceio/btrace

TP500Forms, Testar adds a *form-filling* action, selecting an input profile based on its weight when a form is detected.

Each experimental configuration was repeated 30 times to deal with randomness, with Testar restoring the SUT's initial state after each sequence. This setup was used to evaluate the influence of sequence length on coverage metrics and the relationship between code smells and traditional coverage metrics. One experienced tester with prior knowledge of Yoho conducted manual testing, thoroughly exploring the system during a one-day session.

5 RESULTS

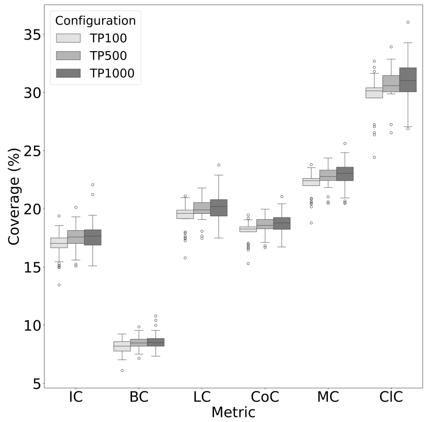
This section presents the results obtained to understand the influence of sequence length on traditional test adequacy metrics, the relationship between code smells and traditional coverage metrics, and the comparison of random with manual testing.

5.1 RQ1:Number and Length of Test Sequences

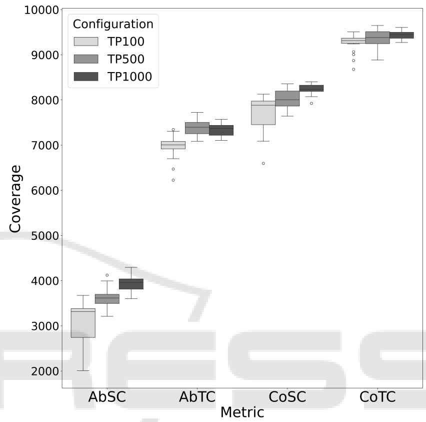
Figure 2a shows box plots comparing the traditional coverage metrics across the three test runs. The graphs reveal a consistent trend across metrics, with coverage generally increasing from TP100 to TP1000, though the magnitude varies by metric. Instruction Coverage (IC) and Branch Coverage (BC) show lower percentages with minimal variation across test processes. Line Coverage (LC) and Complexity Coverage (CoC) show moderate coverage with slightly more variability, while Method Coverage (MC) and Class Coverage (ClC) show the highest coverage levels and the most noticeable differences across configurations. TP1000 consistently achieves higher median coverage and often larger variability, particularly for MC and ClC. Several metrics, especially ClC, show outliers, indicating exceptionally high or low coverage in some test runs.

For the state coverage metrics, Figure 2b illustrates how test runs with longer sequences lead to significantly better coverage of both abstract and concrete states and transitions.

Figure 3 shows the distribution of unique code smells covered by each configuration. Similarly, the data suggest a trend towards higher code smell coverage with test processes featuring longer sequences. A detailed analysis revealed that 40 code smells were covered by at least one run in each test process. Although TP1000 covered more code smells on average, three smells were never covered by this test process. TP100 and TP500 uniquely covered a smell related to the *Delete Post* functionality, while TP500 uniquely covered two smells associated with *Delete User*. The three aforementioned code smells are classified as Major severity and fall under the Conditionals Complexity subcategory.



(a) Code Coverage



(b) State Model Coverage

Figure 2: Distribution of coverage metrics.

Figure 4 shows the distribution and density of code smell occurrences across test processes. Occurrences refer to the total number of times code with existing code smells is executed during testing. TP100 shows the lowest total of occurrences, with a narrow distribution centred around 7500 occurrences per run. In contrast, TP500 and TP1000 configurations present broader distributions with longer upper tails, suggesting these configurations occasionally produce runs with more interactions with smelly code.

Statistical analysis was done to test whether the observed differences in metrics across the test configurations (TP100, TP500, and TP1000) are meaningful or likely due to random variation. As shown in Table 4, we used the Kruskal-Wallis test to determine whether there was at least one significant dif-

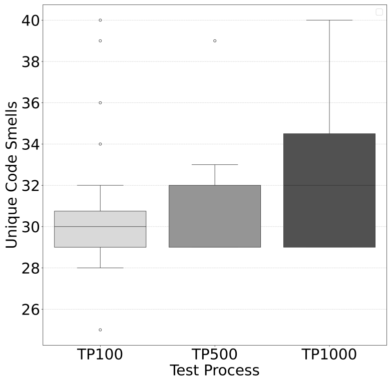


Figure 3: Distribution of code smell coverage.

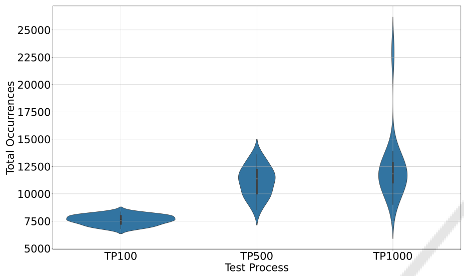


Figure 4: Distribution of code smells occurrences.

ference among the test configurations for each metric without assuming normal distributions. We followed up with Mann-Whitney U tests for pairwise comparisons, while Dunn's test further confirmed significance across multiple comparisons.

Code coverage metrics across the three configurations revealed significant differences in several metrics. TP100 showed significantly lower coverage across all metrics (except IC and BC) than TP1000 and TP500, with moderate effect sizes (0.31 to 0.38), indicating practically meaningful differences. No significant differences were found between TP1000 and TP500 for traditional metrics. Regarding state metrics, Kruskal-Wallis tests indicated significant differences across all metrics ($p < 0.001$). Post-hoc analysis revealed that TP100 resulted in significantly lower coverage than TP500 and TP1000 for both AbSC and AbTC, with large effect sizes highlighting the substantial impacts of shorter sequences on coverage levels. Kruskal-Wallis and Dunn's tests confirm significant differences in code smell occurrences among the configurations, with large effect sizes in comparisons between TP100 and the other test processes.

Our results show that longer test sequences significantly improve traditional coverage metrics and increase code smell occurrences. Additionally, the distribution pattern suggests that longer sequences enhance code smell coverage.

RQ1 Answer: *longer random test sequences improve traditional coverage metrics and code smell coverage metrics.*

5.2 RQ2: Relationship Between Code Coverage Metrics

To investigate the relationship between coverage metrics, we calculated Spearman's rank correlation coefficients between code smell coverage and each traditional adequacy metric for all configurations. Spearman's correlation is chosen due to the data's non-normal distribution. Results are shown in Table 5.

All correlation coefficients between code smell coverage and traditional code metrics are statistically significant (Table 5a), mostly indicating a moderate correlation. The correlation with state metrics (Table 5b) is generally weak and not statistically significant. This finding suggests that traditional coverage metrics alone might not adequately capture a test suite's effectiveness at uncovering deeper issues like code smells, highlighting the need for complementary metrics or deeper analysis beyond basic coverage percentages.

Testers should consider these correlations when designing test suites and possibly combine traditional metrics with newer, more code-quality-focused metrics. Among traditional metrics, Method and Complexity Coverage show the highest correlations with Code Smell Coverage across all test processes, indicating they are more reliable for exposing quality issues like code smells. However, widely used metrics like Instruction and Branch Coverage appear less reliable as standalone indicators of test quality.

RQ2 Answer: *traditional metrics are useful, but not sufficient alone at reflecting the ability of the test suite to detect deeper quality issues, such as code smells. Code Smell Coverage can be a valuable metric to be considered along with the traditional coverage metrics to obtain a more holistic view of software quality and test effectiveness*

5.3 RQ3: Comparison of Random with Manual Testing

Following the analysis of RQ1 (see Section 5.1), TP500 covered all code smells reached by TP1000 and additional ones while reaching similar code smell coverage in most test runs with fewer resources than TP1000. Therefore, we enhanced TP500 with the form-filling feature to compare it with manual testing.

Figure 5 compares the scriptless testing processes, including the enhanced test process (TP500Forms),

Table 4: Statistical Analysis of Code Coverage Metrics.

Metric	KW[a] p-value	Mann-Whitney U (Effect Size) TP1000 vs TP500	TP1000 vs TP100	TP500 vs TP100	Significant Pairs (M-W U / Dunn's test)
CSC	0.28	0.71 (0.05)	0.13 (0.22)	0.22 (0.18)	-
CSO	**0.001**	0.08 (0.27)	**0.001 (1)**	**0.001 (1)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b,c}
LC	**0.049**	0.77 (0.04)	**0.04 (0.31)**	**0.03 (0.33)**	TP1000 vs TP100^{b}, TP500 vs TP100^{b}
IC	0.13	0.89 (0.02)	0.09 (0.26)	0.08 (0.27)	-
BC	0.09	0.71 (0.06)	0.051 (0.29)	0.07 (0.27)	-
CoC	**0.02**	0.65 (0.07)	**0.02 (0.36)**	**0.01 (0.38)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b}
MC	**0.01**	0.70 (0.06)	**0.01 (0.37)**	**0.01 (0.38)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b,c}
ClC	**0.03**	0.65 (0.07)	**0.02 (0.35)**	**0.03 (0.34)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b}
AbSC	**0.001**	**0.001 (0.74)**	**0.001 (0.99)**	**0.001 (0.78)**	all pairs^{b,c}
CoSC	**0.001**	0.28 (0.16)	**0.001 (0.88)**	**0.001 (0.89)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b,c}
AbTC	**0.001**	**0.001 (0.64)**	**0.001 (0.94)**	**0.001 (0.45)**	all pairs^{b,c}
CoTC	**0.001**	0.25 (0.18)	**0.001 (0.68)**	**0.04 (0.31)**	TP1000 vs TP100^{b,c}, TP500 vs TP100^{b,c}

[a] KW: Kruskal-Wallis test
[b] Significant according to Mann-Whitney U test ($p < 0.05$)
[c] Significant according to Dunn's test with Bonferroni correction ($p < 0.05$)
Note: Bold values indicate statistical significance ($p < 0.05$). Effect sizes (Cliff's delta) a

Table 5: Spearman's Correlation: Code Smell Coverage vs Traditional Metrics.

(a) Code Coverage Metrics

Conf.	IC	BC	LC	CoC	MC	ClC
TP100	.459*	.393*	.508**	.611***	.664***	.578***
TP1000	.597***	.627***	.597***	.586***	.585***	.590***
TP500	.401*	.536**	.433*	.451*	.435*	.455**

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(b) State Coverage Metrics

Conf.	AbSC	AbTC	CoSC	CoTC
TP100	-.049	.043	-.050	-.048
TP1000	.078	-.097	-.256	-.224
TP500	.150	.212	.302	.243

Table 6: Manual Testing Coverage Results.

Metric	Manual Testing	TP500Forms Average	TP500Forms Max
IC	43.03%	43.21%	54.50%
BC	20.53%	17.42%	21.95%
LC	49.48%	47.76%	60.01%
CC	42.09%	39.20%	49.22%
MC	51.47%	48.00%	60.27%
ClC	57.47%	72.28%	82.95%
CSC	74	57.9	82

and the manual testing results, regarding Code Smell Coverage. TP500Forms significantly outperformed the original TP500 test process, closing the gap with the 74 code smells detected by manual testing. Some runs of TP500Forms even detected up to 82 unique code smells, surpassing the manual testing results.

The coverage metrics in Table 6 provide further insight. While manual testing achieved slightly higher or similar code coverage, TP500Forms exhibited broader class exploration. Furthermore, TP500Forms discovered more unique code smells (101) than manual testing (88), suggesting that the enhanced approach can match the thoroughness of manual testing in terms of traditional adequacy metrics and surpass it for code smell coverage.

We analysed the types of code smells covered (or not) by random or manual testing, as shown

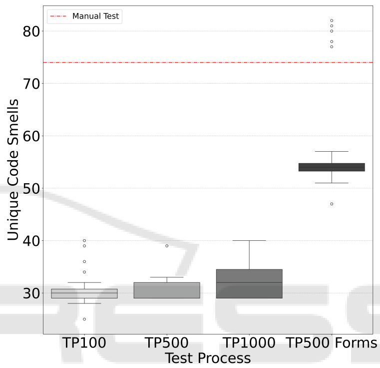


Figure 5: Distribution of code smell coverage.

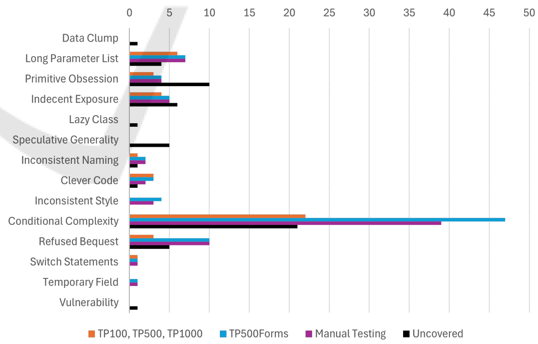


Figure 6: Coverage of Code Smell types.

in Figure 6. Scriptless approaches (TP100, TP500, TP1000, and TP500Forms) covered 12 code smells that were not reached during manual testing. Two code smells were of Minor severity, categorised as Clever Code and Inconsistent Style, while the remaining ten were classified as Conditional Complexity with Major severity. These smells were associated with two specific application functionalities (deleting feed and task commenting), whose user stories were not covered in manual testing.

Despite not consistently outperforming manual testing in individual runs, the TP500Forms configuration, when considered in aggregate across all runs, covered three additional code smells that were not reached during manual testing or by the other random test processes. Two of these code smells were classified as Major. One of the new covered smells was reached due to a random input combination of a filtering functionality within the SUT. This was the only newly reached code smell that did not result from the predefined form field values. Notably, every code smell covered by manual testing was also covered by at least one test run of TP500Forms.

In summary, random testing identified code smells missed by manual testing, demonstrating (again (Vos et al., 2021; Jansen et al., 2022)) its potential as a complementary approach. However, random testing struggled with forms requiring specific inputs, which manual testing handled better. The enhanced form-based approach demonstrated comparable and even surpassed manual testing by covering all manually reached smells and additional ones.

RQ3 Answer: *the findings suggest that random testing offers promising complementary effectiveness in test coverage and identifies unique smells that manual testing might overlook.*

6 DISCUSSION

To understand the impact of adopting random testing and introducing the code smell coverage metric on Marviq's QA process, we held two one-hour focus groups with three test engineers. Marviq shared that these additions significantly enhanced their workflow. While manual testing leverages testers' domain expertise, random testing complements it by uncovering unexpected navigation paths, providing a balanced approach that strengthens quality control.

The team further emphasised the value of scriptless testing as a complementary tool within their established QA practices. Running these scriptless tests overnight and integrating them into the CI/CD pipeline enables a continuous and efficient testing cycle. This not only enhances software robustness but also supports the move toward continuous delivery, reducing the need for separate acceptance testing and optimising both time and effort per release.

Marviq also observed that once configured for a specific project—as demonstrated with the Yoho project (Section 4.2.1), the testing setup can be easily adapted for other projects using similar technologies, making it a scalable and reusable solution.

Finally, Marviq noted that monitoring coverage metrics linked to code smells is an effective early warning system. This proactive approach helps the team address quality concerns early in development, supporting the delivery of more robust software.

7 THREATS TO VALIDITY

We discuss the threats to the validity of our study following (Wohlin et al., 2012) and the mitigation actions taken to control them within our possibilities.

Internal Validity. The scriptless GUI testing process's randomness poses a potential threat. The specific sequence of actions generated during the testing process may influence the coverage of code smells, with different executions yielding different levels of coverage. To mitigate this threat, we ran multiple testing sessions with varied configurations to observe trends and reduce the impact of randomness.

External Validity. A limitation of this study is the use of a single SUT, selected for its role as a core system for the company with functionalities commonly used in web applications. While we advocate that the selected SUT is representative of other industrial web applications, the results may not generalise to other applications, such as mobile or desktop software. Additionally, reliance on SonarQube for code smell detection and Testar for GUI testing may limit generalisation, as other tools might yield different results. Future research should replicate this approach with diverse applications and testing tools to validate the generalisation of our findings.

Construct Validity. This study uses code smells as a proxy for software quality and testing effectiveness. Although widely recognised as indicators of maintainability and quality issues, code smells may not always directly correlate with system defects. Additionally, we rely on SonarQube for code smell detection, which may not capture all relevant issues. To address this, we ensured that detected smells were representative of common issues, but the limitations of the tools should be acknowledged.

Conclusion Validity. One potential threat is the sample size of the testing actions and configurations. Although we executed 10,000 actions, this may be insufficient to generalise findings across all possible scenarios in the application. Moreover, the impact of configuration settings on code smell coverage requires cautious interpretation, as some configurations may favour certain types of code smells. To mitigate this, we conducted experiments with varied configurations, but future work should explore a wider range of parameters to draw more robust conclusions.

8 CONCLUSIONS

This study explored the potential of random scriptless GUI testing as a complementary approach to traditional testing in an industrial setting, focusing on Marviq's Yoho web application. Our results indicate that increasing the length of random test sequences enhances both traditional coverage metrics and code smell coverage significantly, suggesting that longer test sequences can lead to more thorough and effective testing even within resource constraints.

The findings further suggest that while traditional coverage metrics offer valuable insights into testing adequacy, they are insufficient to capture the full scope of quality issues, particularly code maintainability. By integrating code smell detection with traditional metrics, we gain a more comprehensive perspective on software quality, addressing areas of technical debt and maintainability that may be overlooked with conventional coverage alone.

Moreover, random GUI testing also demonstrated a unique strength in identifying code smells missed by manual testing, including some critical ones. While manual testing benefits from the tester's domain knowledge, random testing offers the potential of unexpected navigation paths. Therefore, the study highlights the complementary role of random testing alongside manual testing, as random testing effectively identifies unique code smells that manual efforts might miss. This synergy between testing methods enhances overall test coverage, potentially reducing reliance on manual testing and enabling a more resource-efficient approach to quality assurance in software development.

In conclusion, combining functional coverage metrics with maintainability-focused analyses, such as code smell detection, provides a robust and efficient testing framework that better aligns with industrial needs. This approach offers a deeper and more accurate assessment of software quality, covering aspects of both functionality and maintainability.

Future work will extend our experimentation across a broader range of web applications and software platforms and different industrial contexts with varying resources, system configurations, and maintenance requirements. This expansion will help to improve the generalizability and reliability of our findings beyond the specific conditions of this study. Additionally, we aim to develop an AI-driven agent that guides GUI exploration by targeting areas of broad smell coverage, potentially increasing the precision and effectiveness of code smell detection. This AI-guided approach could pave the way for more efficient and quality-focused testing methodologies.

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[4]https://enactest-project.eu/

[5]https://www.ivves.eu

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