

Context-Enhanced LLM-Based Framework for Automatic Test Refactoring

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Test smells arise from poor design practices and insufficient domain knowledge, which can lower the quality of test code and make it harder to maintain and update. Manually refactoring of test smells is time-consuming and error-prone, highlighting the necessity for automated approaches. Current rule-based refactoring methods often struggle in scenarios not covered by predefined rules and lack the flexibility needed to handle diverse cases effectively. In this paper, we propose a novel approach called UTREFACTOR, a context-enhanced, LLM-based framework for automatic test refactoring in Java projects. UTREFACTOR extracts relevant context from test code and leverages an external knowledge base that includes test smell definitions, descriptions, and DSL-based refactoring rules. By simulating the manual refactoring process through a chain-of-thought approach, UTREFACTOR guides the LLM to eliminate test smells in a step-by-step process, ensuring both accuracy and consistency throughout the refactoring. Additionally, we implement a checkpoint mechanism to facilitate comprehensive refactoring, particularly when multiple smells are present. We evaluate UTREFACTOR on 879 tests from six open-source Java projects, reducing the number of test smells from 2,375 to 265, achieving an 89% reduction. UTREFACTOR outperforms direct LLM-based refactoring methods by 61.82% in smell elimination and significantly surpasses the performance of a rule-based test smell refactoring tool. Our results demonstrate the effectiveness of UTREFACTOR in enhancing test code quality while minimizing manual involvement.

Additional Key Words and Phrases: Test Smells, Refactoring, Large Language Models

ACM Reference Format:

Yi Gao, Xing Hu, Xiaohu Yang, and Xin Xia. 2024. Context-Enhanced LLM-Based Framework for Automatic Test Refactoring. 1, 1 (September 2024), 20 pages. <https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

1 INTRODUCTION

During the software testing process, test code often suffers from **test smells**, which originate from a lack of sufficient domain knowledge by software engineers and the adoption of poor design practices when writing test code. Recent studies [20, 32] have shown that developers tend to prioritize production code over test code, which further contributes to the decline in test code quality. From a software maintenance perspective, test smells in a software system can complicate the test code, making it harder to read, understand, and update. This complexity can ultimately lead to a decline in software product quality and reduced developer productivity. Test smells can be removed through test refactoring—a process of improving the internal structure of the code without altering

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XXXX-XXXX/2024/9-ART \$15.00

<https://doi.org/10.1145/nnnnnnnn.nnnnnnnn>

the software's external behavior [22, 32, 35]. Numerous empirical studies [20, 25, 28, 31, 32, 35, 36] have highlighted the importance of test refactoring, and developers widely accept the refactored tests, and both developers and testers are increasingly recognizing the negative impact of test smells. They widely agree that test quality improves significantly once test smells are eliminated. Additionally, many studies [17, 18, 21, 24, 29, 30, 33, 37–39] have proposed test smell detection tools across programming languages such as Java, Scala, and Python, while also evaluating the impact of test smells on the software development process.

However, manual refactoring of test code remains time-consuming, inefficient, and is prone to errors, underscoring the need for automated tools to address a broader range of test smells. Although there is a clear demand for such tools, only a few open-source options exist for automatic test refactoring [22]. Those tools primarily handle basic and limited types of test smells, leaving many types unaddressed. At present, no tool is capable of efficiently and automatically eliminating all types of test smells.

Given the remarkable capabilities of large language models (LLMs) in understanding, generating, and reviewing code, they might have the potential to play a key role in test refactoring tasks. In this paper, we explore the potential of open-source LLMs to automate unit test refactoring and propose a approach for automatically eliminating test smells in software projects. However, several challenges must be addressed to achieve this goal:

Challenge 1: How to guide the LLM to eliminate test smells in an expected way? Refactoring aims to optimize code structure without altering the original functionality and logic. However, LLMs may generate hallucinations during the refactoring process, producing random code segments that introduce syntax or semantic errors. Thus, the first challenge is how to direct the LLM to follow predefined steps for refactoring, ensuring it remains consistent and produces the intended results.

Challenge 2: How to eliminate multiple test smells simultaneously? Since there are many types of test smells, and multiple smells may exist within a single test method, different removal orders can lead to different refactoring outcomes. The challenge lies in ensuring that all identified test smells are accurately and comprehensively eliminated.

In this paper, we propose a context-enhanced, LLM-based automatic test refactoring approach for Java projects. Our proposed approach, named UTREFACTOR, first extracts the project's test code and related context information, such as the functions and classes under test. We then build an external knowledge base that supports test smell elimination, which includes test smell definitions and descriptions, DSL-based refactoring rules, and other relevant contextual information. Next, we simulate the manual refactoring process typically followed by developers or testers. Using a chain-of-thought approach, we guide the LLM through understanding the test's intent, identifying the test smells, and following the DSL-defined refactoring steps to refactor the test code. Additionally, we design a checkpoint mechanism to ensure more thorough smell elimination, particularly when multiple test smells are present in a single test.

We evaluate UTREFACTOR on six popular Java open-source projects collected from GitHub. In our experiments, we detect 879 tests with smells out of 9,149 tests and apply smell elimination refactoring to them. The results show that UTREFACTOR reduces the number of test smells from 2,375 to 265, achieving a reduction rate of 89%. This represents a 61.82% improvement in performance compared to directly using an LLM for test refactoring. The main contributions of this paper are as follows:

- We propose a novel approach that leverages code context information and integrates refactoring DSL rules to enhance the test refactoring capabilities of LLMs, enabling the automatic elimination of test smells and improving the quality of unit tests.

- We develop UTREFACTOR, a tool that assists developers and testers in automatically refactoring test code in Java projects. It supports various levels of granularity, including single tests, test files, and entire projects.
- We evaluate UTREFACTOR on 879 tests across six open-source projects, reducing the number of test smells from 2,375 to 265, outperforming baselines in effectiveness.

2 MOTIVATION

Developers often prioritize maintaining production code while neglecting the maintenance of test code, which can lead to increased maintenance costs, such as those associated with regression testing. [32]. To illustrate the quality issues in test code, we analyze the Gson project [8], a popular Java library developed by Google, which has over 23.2k stars on GitHub and continues to be actively maintained, including its test code. Figure 1 presents an intuitive example from the Gson's `JsonObjectTest` class. According to the test smell types defined by `tsDetect` [15], this test has been identified with three distinct smell: ① **Eager Test**: This is a common and challenging type of smell to refactor. It occurs when a test method invokes several methods from the production code, making it harder to understand, maintain, and modify the test code effectively, as the test's purpose becomes less clear. In this example, this test suffers from the *Eager Test* smell because it is testing multiple behaviors—adding(`add`), removing(`remove`), and checking(`has` and `get`) properties—within a single test method. This violates the principle of *Single Responsibility Principle (SRP)* [14]. Each test method should focus on testing a specific behavior or function. Otherwise, it becomes harder to pinpoint the root cause of failures and reducing test clarity. To address this, each of these behaviors should be split into separate test methods to ensure that the test remains focused and maintainable. ② **Duplicate Assert**: In this example, the repeated use of the same parameter `propertyName` across multiple assertions leads to the identification of a *Duplicate Assert* smell. Eliminating this smell can be achieved by either splitting the original test or transforming it into a *Parameterized Test*, which removes the need for duplicate assertions by declaring parameterized values in an annotation and executing the test method multiple times. ③ **Assertion Roulette**: This is another common smell, indicating that multiple assertions in a test which are lack of clear identification of the reasons for failure, and make it difficult to locate the failing assertion. To address this, each assertion should be supplemented with descriptive information that clarifies its purpose. This allows developers to quickly identify and fix issues when the test fails.

These test smells demonstrate the potential risks in test code that can compromise its quality and maintainability, highlighting the importance of systematically eliminating the existing smells. Our tool, UTREFACTOR, is designed to automatically refactor unit tests and eliminate test smells, thereby improving the quality of test code in existing software projects. Figure 1(right) shows tests refactored using UTREFACTOR, which have successfully removed the three identified test smells. Developers or testers can use UTREFACTOR to refactor individual unit tests, single test files, or all tests in a project at once to eliminate smells and improve the overall quality of the software's code.

Another potential benefit of automated test refactoring lies in its impact on LLMs, many of which are trained on data from open-source communities. By improving the quality of the test code that serves as training data, we can enhance the performance of LLMs in tasks such as test generation. For instance, during the data preprocessing phase, we can refactor test code that contains smells and use the cleaned, refactored code as training data. This approach may lead to more effective and reliable LLM-generated tests.

3 APPROACH

This section presents the details of our proposed approach UTREFACTOR. As shown in Figure 2, which can be divided into three main steps:

```

Original Test


```

 @Test
 public void testAddingAndRemovingObjectProperties() {
 JsonObject jsonObj = new JsonObject();
 String propertyName = "property";
 assertThat(jsonObj.has(propertyName)).isFalse();
 assertThat(jsonObj.get(propertyName)).isNull();

 JsonPrimitive value = new JsonPrimitive("blah");
 jsonObj.add(propertyName, value);
 assertThat(jsonObj.get(propertyName)).isEqualTo(value);

 JsonElement removedElement = jsonObj.remove(propertyName);
 assertThat(removedElement).isEqualTo(value);
 assertThat(jsonObj.has(propertyName)).isFalse();
 assertThat(jsonObj.get(propertyName)).isNull();
 assertThat(jsonObj.remove(propertyName)).isNull();
 }

```



1 Eager Test  
The test invokes several methods of the production object. This smell results in difficulties in test comprehension and maintenance.



2 Duplicate Assert  
The test contains more than one assertion statement with the same parameters. (jsonObj.get(propertyName) occurs three times.)



3 Assertion Roulette  
The test has multiple non-documented assertions.


```

```

Refactored Test1


```

 @Test
 public void testJsonObjectHasPropertyInitiallyFalse() {
 JsonObject jsonObj = new JsonObject();
 String propertyName = "property";
 assertThat(jsonObj.has(propertyName)).as("Property should not exist initially").isFalse();
 assertThat(jsonObj.get(propertyName)).as("Property value should be null initially").isNull();
 }

```


```

```

Refactored Test2


```

 @Test
 public void testJsonObjectAddProperty() {
 JsonObject jsonObj = new JsonObject();
 String propertyName = "property";
 JsonPrimitive value = new JsonPrimitive("blah");
 jsonObj.add(propertyName, value);
 assertThat(jsonObj.get(propertyName)).isEqualTo(value);
 }

```


```

```

Refactored Test3


```

 @Test
 public void testJsonObjectRemoveProperty() {
 JsonObject jsonObj = new JsonObject();
 String propertyName = "property";
 JsonPrimitive value = new JsonPrimitive("blah");
 jsonObj.add(propertyName, value);
 JsonObject removedElement = jsonObj.remove(propertyName);
 assertThat(removedElement).as("Removed element should match added value").isEqualTo(value);
 assertThat(jsonObj.has(propertyName)).as("Property should not exist after removal").isFalse();
 assertThat(jsonObj.get(propertyName)).as("Property value should be null after removal").isNull();
 assertThat(jsonObj.remove(propertyName)).as("Removing non-existent property should return null").isNull();
 }

```


```

Fig. 1. An example of test refactoring within the Gson.

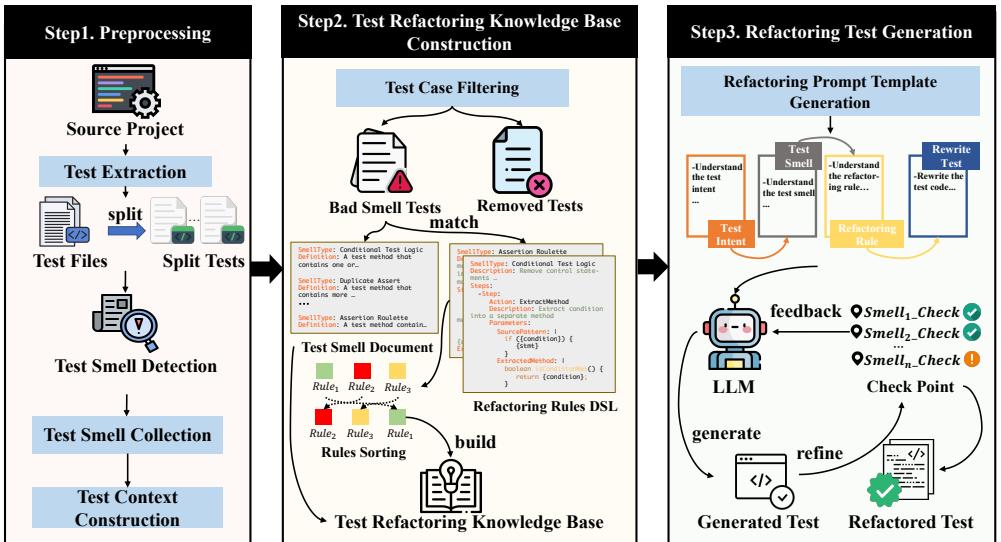


Fig. 2. Overview of our approach.

Step 1 Preprocessing. We begin by extracting the test code from the project and detecting all test smells present. For tests that need to be refactored due to the presence of smells, we also extract relevant code context (such as the tested functions and classes) during this step, treating this context as external knowledge for the LLM.

Step 2 Test Refactoring Knowledge Base Construction. In this step, we design the types and definitions of test smells to serve as external knowledge that the LLM can reference. Additionally, we use a Domain-Specific Language (DSL) [27] to define corresponding refactoring rules for each type of test smell, constructing a comprehensive refactoring knowledge base.

Table 1. Extracted test-related context information from the project.

| Items | Description |
|-------------------------------|--|
| Package Name | The name of the package where the focal method is located, eg., org.jsoup.parser |
| Focal Class | The name of the class containing the focal method. eg., public class Parser |
| Focal Method Signature | The signature of the focal method. eg., public static Document parse(String html, String baseUri) |
| Focal Method Comment | The code comment for the focal method. eg., Parse HTML into a Document. |
| Other Invoke Methods | The signatures of other methods invoked in the test. eg., public static String unescapeEntities(String string, boolean inAttribute). |

Step ③ Refactored Test Generation. This step focuses on generating the refactored test code. We design a specialized prompt template tailored for the test refactoring task. Moreover, we employ the Chain-of-Thought (CoT) [6] reasoning approach and propose a checkpoint mechanism to improve the LLM’s performance in refactoring test code.

3.1 Preprocessing

As shown in Figure 2, during this step, we primarily focus on extracting the test code, detecting the test smells within it, and collecting relevant test context information.

3.1.1 Test Extraction. First, UTREFACTOR automatically gathers all test files from the test directory (e.g., src/test) within a given Java project. To avoid unnecessary detection of code smells and refactoring overhead, during the test extraction process, we analyze whether the test files contain at least one method annotated with @Test, and automatically filter out files that do not have the @Test annotation. Besides, to analyze the focal methods in a fine-grained approach and meet the requirements of test smell detection, we collect the corresponding classes under test in this step. Specifically, we strip the prefix and suffix Test from the test file names (e.g., ParserTest→Parser), and use this as an index to search for matching class files in the src/main directory. If a match is successful, the test file and the corresponding class under test are paired and collected together.

3.1.2 Test Smell Detection. To detect test smells present in the project, we integrate the *tsDetect* [30], an automated test smell detection tool for Java software systems.

Refining Detection Granularity. Our UTREFACTOR performs refactoring at the level of individual test methods, refactoring one test at a time. However, the *tsDetect* operates at a file-level granularity, meaning it can detect test smells in a test file as a whole but cannot pinpoint smells within specific test methods. To support the detection of smells at the level of individual test methods, we refine the test smell detection granularity. Specifically, we employ a split-and-merge approach: before smell detection, we split each test file into multiple sub-files, with each sub-file containing a single test method and its necessary context. This ensures that *tsDetect* can analyze each test method independently. After the refactoring process is completed, these sub-files are merged back together into a complete test file based on the original split index.

3.1.3 Test Context Collection. Since refactoring operations are aimed at optimizing the code structure without altering its functional logic, it is crucial to ensure that the LLM has a sufficient understanding of the test code's functionality before refactoring. Moreover, Yuan et al. [40] has demonstrated that providing additional test context can significantly enhance the performance of LLMs in test code generation tasks. Inspired by these findings and applying them to the task of refactoring test code, we extract relevant contextual information from tests that exhibit smells and use it as external knowledge to help the LLM better comprehend the original test's intent, as shown in Table 1.

In this step, we extract the contextual information for each test that requires refactoring. During the subsequent refactoring steps, this information is integrated into the refactoring prompt template as a knowledge source to assist the LLM in accurately understanding the test's original purpose.

3.2 Test Refactoring Knowledge Base Construction

In this step, we design the test smell types and corresponding refactoring rules as applicable external knowledge, aiming to enhance the LLM's understanding of test smells and effectively eliminate those present in unit tests.

3.2.1 Test Smell Knowledge. In the smell detection step, we integrate *tsDetect*, which uses the 19 types of test smells defined by Peruma et al. [30]. Although they define test smells and provide relevant code examples, the definition of test smells is not standardized across existing research, and the types and numbers of smells can vary between studies.

Additionally, LLMs are trained on data from various sources, such as blogs and GitHub repositories, which can lead to significant differences between LLMs in terms of training data. This variability leads to inconsistencies in how LLMs interpret test smells, which in turn affects the effectiveness of the refactoring process. To illustrate this issue, we use *LLaMA-70b* [12]. As shown in Figure 3, when asked about the meaning of specific test smells, the LLM's responses deviate from our expectations. For example, *tsDetect* does not include **Fragile Test** in its list of smells. Additionally, for the **Mystery Guest** smell, *LLaMA-70b* provides a vague explanation, whereas *tsDetect* defines it as the presence of unused variables in the *setup/teardown* method. There are also instances where the definitions are similar, but the naming conventions differ. For example, **Missing Assertion** refers to a test method that lacks a test oracle, but in *tsDetect*, this is categorized as **Unknown Test**.

To mitigate the impact of these inconsistencies on the refactoring process, we provide the LLM with a clear and standardized set of test smell definitions before refactoring. Given that Peruma et al. [30] provide comprehensive definitions, explanations, and code examples for 19 test smells in Java, we use these to build part of the external knowledge base for test smells, providing it to the LLM to eliminate inconsistencies in smell interpretation that could impact the refactoring process. For each smell type, we provide a structured definition, including a description of the test smell, its impact, and a pseudocode example to illustrate the concept. During the refactoring process, these standardized smell definitions

Question

As an expert in the field of **test code refactoring**, please enumerate the **types of test code smells** along with their definitions.

Llama3-70B Output

- **Missing Assertion**
A test that lacks assertions, making it impossible to verify the expected behavior.
- **Rigidity Test**
A test that is **difficult** to modify or extend, making it hard to adapt to changing requirements or new functionality.
...
- **Mystery Guest**
A test that uses **complex** or **unclear** setup/teardown, making it hard to understand the test's purpose.

Fig. 3. An example of test smell explanation of the LLM.

guide the LLM's interpretation of the smells present in the test, ensuring consistent and accurate refactoring results.

3.2.2 Test Refactoring Rule DSL. To eliminate the smells present in tests, we design corresponding refactoring rules for each type of smell. We draw on previous manual approaches to eliminating test smells and empirical research on test smell refactoring [16]. Based on these insights and best testing practices, we formalize DSL rules for each type of test smell, which form the foundation of the entire refactoring process. In designing these DSLs, we exclude simple smell types such as *Default Test*, which refers to default test classes automatically created by *Android Studio* when a project is initialized and do not require refactoring. Similarly, we handle *Ignored Test* (tests marked as ignored) and *Empty Test* (tests with empty method bodies) by simply removing the unit tests that exhibit these smells. Finally, we define 13 function-level DSLs for Java test smells, aimed at eliminating smells in unit tests. Since these DSLs determine the methods and steps for eliminating test smells, which is crucial for unit test refactoring, we evaluate the correctness of the DSL design by assessing whether the refactored tests successfully eliminate the smells without introducing new issues. This will be discussed in detail in subsequent sections.

We leverage LLMs to refactor tests with identified smells according to the provided refactoring rules. A common approach is to describe these refactoring rules in natural language as prompts for the LLM. While this approach is straightforward and easy to understand, it presents challenges in practice: natural language can be ambiguous or imprecise, which may lead the LLM to generate code that does not meet expectations, especially when multiple smells are present in a single test. Without a clear strategy to guide the refactoring process, the LLM's behavior can become unpredictable, resulting in inconsistent outcomes. Moreover, the lengthy natural language descriptions required for such complex cases can hinder the LLM's effectiveness in refactoring tests.

To address this issue, we propose using a more precise Domain-Specific Language (DSL)

to express the test smell refactoring rules. The

advantage of using a DSL is that it allows for more precise and standardized descriptions of refactoring steps, thereby reducing the risk of misinterpretation. Additionally, DSLs are typically structured, which facilitates the extension and maintenance of new refactoring rules. In practice, developers can easily add and update refactoring rules within the defined DSL structure. This structured approach ensures that refactorings are consistent, predictable, and less prone to errors, providing a clear framework for expanding the tool to accommodate new test smells and evolving best practices in refactoring.

The DSL we design for test smell refactoring is illustrated in Figure 4. Specifically, the *SmellType* defines the specific category of test smell being addressed, ensuring that the appropriate refactoring strategy is applied. The *Description* provides a concise explanation of how the refactoring will be executed for this smell type. The *Steps* component breaks down the refactoring process into a sequence of actions, enabling a fine-grained, step-by-step approach to modifying the test code.

```

RefactorRule ::= {
    SmellType: String, # Corresponds to the type of test smell
    Description: String,
    Steps: [Step],
    Example: Example,
    Variable: Variable
}

Step ::= {
    Description: String,
    Action: ActionType,
    Parameters: {ParameterName: ParameterValue}
}

ActionType ::= AddAnnotation | ReplaceMethodCall |
AddMessageToAssert | ExtractMethod | RemoveConditional |
ConvertToParameterizedTest | RefactorMethod

ParameterName ::= TargetType | Annotation | TargetMethod |
ReplacementPattern | Import | SourcePattern |
ExtractedMethod | MessagePattern

Example ::= {Before: String, After: String}

Variable ::= {VariableName: String, VariableValue: String}

```

Fig. 4. A hierarchical definition of the DSL structure for test refactoring rules.

| Assertion Roulette | | |
|--|--|---|
| SmellType: Assertion Roulette | Original Code Example | Refactored Code Example |
| <p>Description: Add descriptive messages to assert statements.</p> <p>Steps:</p> <ul style="list-style-type: none"> -Step: <p>Action: AddMessageToAssert</p> <p>Description: Add descriptive message to each assert statement.</p> <p>Parameters:</p> <ul style="list-style-type: none"> MessagePattern: {assertionMessage} | <pre>@Test public void testRoot() { // define span, el, el2 assertEquals("<a>Hello", el.outerHtml()); assertNotNull(span); assertEquals(el, el2); assertEquals("Root of span should be the initial element.", el, el2); }</pre> | <pre>@Test public void testRoot() { // define span, el, el2 assertEquals("=>Hello", el.outerHtml(), "Element outerHtml should match expected output."); assertNotNull("Selected span element should not be null.", span); assertEquals("Root of span should be the initial element.", el, el2); }</pre> |

(a) The definition of DSL rules for eliminating AR (Assertion Roulette) smell

| Magic Number Test | | |
|--|--|---|
| SmellType: Magic Number Test | Original Code Example | Refactored Code Example |
| <p>Description: Extract magic numbers and assign meaningful names.</p> <p>Steps:</p> <ul style="list-style-type: none"> -Step: <p>Action: IdentifyMagicNumbers</p> <p>Description: Identify magic numbers in assertions.</p> <p>Parameters:</p> <ul style="list-style-type: none"> SourcePattern: I assert({magicNumber}, {variable}) -Step: <p>Action: ExtractVariable</p> <p>Description: Extract number to a variable with meaningful name.</p> <p>Parameters:</p> <ul style="list-style-type: none"> SourcePattern: I assert({magicNumber}, {variable}) ReplacementPattern: I int {meaningfulName} = {magicNumber}; assert({meaningfulName}, {variable}) | <pre>@Test public void testIteratorRemovable(){ Attributes a = new Attributes(); a.put("Tot", "a&p"); a.put("Hello", "There"); a.put("data-name", "Jsoup"); Iterator<Attribute> iterator = a.iterator(); Attribute attr = iterator.next(); assertEquals("Tot", attr.getKey()); ... iterator.remove(); assertEquals(2, a.size()); }</pre> | <pre>@Test public void testIteratorRemovable_hasKeyAfterRemove() { Attributes a = new Attributes(); a.put("Tot", "a&p"); a.put("Hello", "There"); a.put("data-name", "Jsoup"); Iterator<Attribute> iterator = a.iterator(); Attribute attr = iterator.next(); assertEquals("Tot", attr.getKey()); ... iterator.remove(); int expectedSize = 2; assertEquals(expectedSize, a.size(), "After removing 'Tot', there should be 2 attributes left"); }</pre> |

(b) The definition of DSL rules for eliminating MNT (Magic Number Test) smell

| Duplicate Assert | | |
|--|---|---|
| SmellType: Duplicate Assert | Original Code Example | Refactored Code Example |
| <p>Description: Eliminate duplicate assertions with parameterized tests.</p> <p>Steps:</p> <ul style="list-style-type: none"> -Step: <p>Action: ConvertToParameterizedTest</p> <p>Description: Convert test method to a parameterized test method.</p> <p>Parameters:</p> <ul style="list-style-type: none"> TargetType: Method -Step: <p>Action: AddAnnotation</p> <p>Description: Declare parameterizable values in @CsvSource annotation.</p> <p>Parameters:</p> <ul style="list-style-type: none"> TargetType: Method Annotation: @CsvSource({ "paramValues" }) -Step: <p>Action: ModifyAssert</p> <p>Description: Use parameterized values.</p> <p>Parameters:</p> <ul style="list-style-type: none"> SourcePattern: I public void T() { {stmts} } ReplacementPattern: I public void T({params}) { {refactoredStmts} } | <pre>@Test public void testWholeText() { Document doc = Jsoup.parse("<p>Hello\nthere &nbsp; </p>"); assertEquals(" Hello\nthere ", doc.wholeText()); doc = Jsoup.parse("<p>Hello \n there</p>"); assertEquals("Hello \n there", doc.wholeText()); doc = Jsoup.parse("<p>Hello <div>\n there</div></p>"); assertEquals("Hello \n there", doc.wholeText()); }</pre> | <pre>@ParameterizedTest @CsvSource{ "<p>Hello\nthere &nbsp; </p>", "<p>Hello \n there</p>, Hello\n there", "<p>Hello <div>\n there</div></p>, Hello \n there" } public void testWholeText(String input, String expected) { Document doc = Jsoup.parse(input); assertEquals("The whole text does not match the expected value.", doc.wholeText(), is(expected)); }</pre> |

(c) The definition of DSL rules for eliminating DA (Duplicate Assert) smell

Fig. 5. DSL rules for refactoring three types of test smells, accompanied by code examples illustrating the test code before and after refactoring.

Additionally, the *Example* provides before-and-after code snippets to demonstrate the practical application of the refactoring, aiding in both understanding and verification. Finally, *Variables* parameterize the refactoring logic, offering flexibility and reusability across different test cases. With this structure, the DSL systematically defines and executes complex code refactoring operations, which facilitates the automation of the test refactoring process.

Next, we present specific refactoring rules for test smells. Figure 5 illustrates three concrete examples of these refactorings. For example, when a test contains multiple assert statements without descriptive messages, it is flagged with the *Assertion Roulette* smell. During refactoring, the test matches the DSL rule for the type *Assertion Roulette*. This rule guides the refactoring process by specifying the action *AddMessageToAssert*, which involves adding meaningful descriptive messages to each assert statement. Another example is when a test is identified with the *Duplicate Assert* smell. In this case, the test matches the corresponding DSL rule for *Duplicate Assert*, which outlines a three-step refactoring process to eliminate the smell: **Step 1** Replace the @Test annotation with @ParameterizedTest to enable parameterized testing. **Step 2** Add the @CsvSource annotation. This allows additional test cases to be added as parameters in @CsvSource, eliminating the need for multiple assertEquals statements. **Step 3** Reduce duplicate code by writing the test logic only once. Parameterized testing makes the test cases more intuitive and clearly expresses the relationship between different inputs and expected outputs.

These rules are then provided to the LLM as external knowledge during the refactoring process, guiding the LLM to refactor the test according to the predefined rules.

3.2.3 Sorting Refactoring Rules. Considering that a single test often exhibit multiple types of smells, it is crucial to determine the appropriate order of refactoring operations, as the sequence can significantly impact the effectiveness of the final test code refactoring. To address this, we categorize the test smell refactoring rules and assign them an execution priority. The LLM is then instructed to eliminate test smells according to their priority, from highest to lowest.

We have classified refactoring operations into three categories based on their characteristics: *Removal*, *Structural Optimization*, and *Functional Optimization*. **1 Removal:** This category includes smells that require the test to be removed from the refactoring list rather than undergoing structural adjustments. Examples include *EmptyTest* (test method with an empty body), *Unknown Test* (test without assertions), and *Default Test* (automatically generated default tests). Prioritizing removal operations helps to avoid unnecessary refactoring efforts for tests that do not contribute to code quality. **2 Structural Optimization:** This category focuses on altering the existing structure of the test code. Examples include *Eager Test*, where a test method calls multiple methods of the production object, and *Duplicate Assertion*, where identical assertions are repeated within the same test method. **3 Functional Optimization:** This category targets improvements to assertion statements, such as *Assertion Roulette* (where multiple assertions lack descriptive messages).

Structural Optimizations take precedence over *Functional Optimization* because a well-structured test provides a solid foundation for functional improvements. For instance, the *Assertion Roulette* refactoring rule involves adding descriptive messages to assertions. and the *Magic Number Test* refactoring rule extracts numeric literals into named variables. However, the *Duplicate Assertion* refactoring rule eliminates duplicate assertions using parameterized tests, which could render the optimizations of *Assertion Roulette* unnecessary if performed afterward. Therefore, it is crucial to refactor *Duplicate Assertion* before applying other functional optimizations.

By following this prioritized refactoring approach, we ensure that the test code is systematically improved, starting with essential removals, followed by structural enhancements, and concluding with functional refinements. This strategy optimizes the LLM's ability to perform accurate and comprehensive refactoring.

3.3 Refactoring Test Generation

In this final step, we generate the refactored test code using the specially designed prompt template. The template guides the LLM in applying the refactoring rules to eliminate the identified smells from the test code.

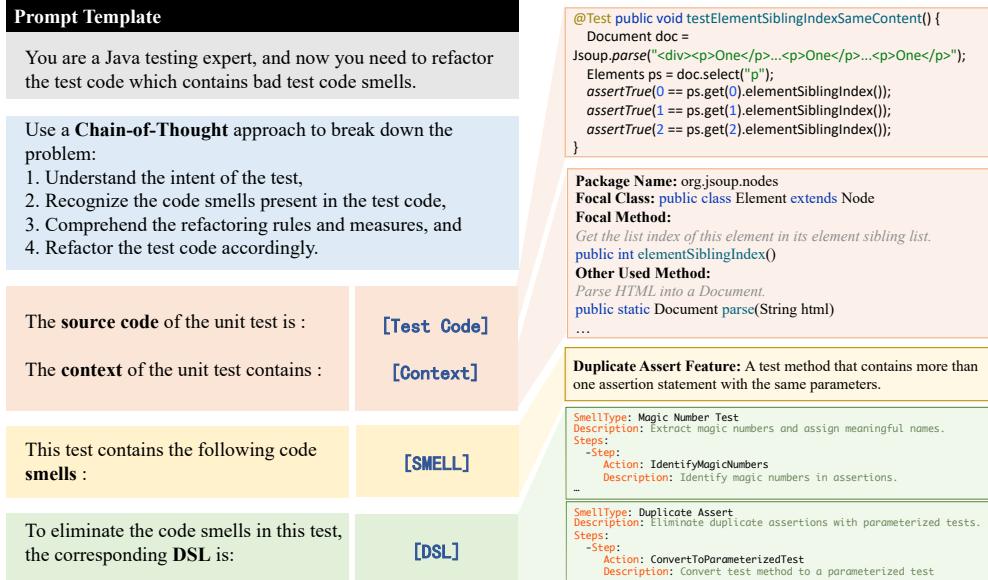


Fig. 6. The Prompt Template used for test smell elimination, along with corresponding examples of prompts.

3.3.1 Test Refactoring Prompt Design. Typically, when a developer or tester refactors a test, they follow a process that involves: ① Understanding the intent of the test code, including what the focal method does and how the assertions verify its behavior. ② Identifying the quality issues in the current test, specifically recognizing any smells present. ③ Most importantly, determining how to refactor the test to eliminate these smells. ④ Rewriting the test code accordingly. Our approach is designed around these steps and is divided into four steps. This four-step strategy is based on the Chain-of-Thought (CoT) paradigm, which enhances LLM reasoning capabilities by encouraging step-by-step thinking, leading to better outcomes in tasks such as extraction and reasoning [23].

As illustrated in Figure 6, the complete prompt template based on CoT is designed to improve the LLM’s ability to refactor tests. In guiding the LLM through the refactoring process, we simulate the actual steps a developer takes. First, to understand the test’s intent, we provide the LLM with the test code along with relevant context, such as the tested class and method signatures. Next, we present the identified smells in the test and their corresponding definitions. Crucially, we supply the DSL-defined refactoring rules tailored to each smell type. Finally, with this external knowledge, the LLM proceeds to refactor the test. This structured approach ensures that the LLM closely follows a logical and thorough process, much like a human developer or tester, resulting in more effective and accurate test refactoring.

3.3.2 Checkpoint Mechanism. We observed that when a test contains multiple smells, even with sufficient information provided, the LLM may still miss eliminating some of the smells during refactoring. For example, in the `testSizeWhenHasInternal` function from the Jsoup project, the test has four identified smells: *Assertion Roulette*, *Eager Test*, *Duplicate Assert*, and *Magic Number Test*. Despite explicitly instructing the LLM to address all four types of smells in the prompt, in practice, the LLM often fails to fully refactor tests with multiple smells.

To address this issue and mitigate incomplete refactoring by the LLM, we design a checkpoint mechanism that allows the LLM to self-verify the completeness of its refactoring process. Specifically,

Table 2. Test refactoring dataset (#**TSmell** - number of tests with smells, #**TS Num** - number of test smells).

| Project | Tests | #TSmell | #TS Num | LOC |
|----------------------|--------------|----------------|----------------|----------------|
| Commons-cli [3] | 334 | 85 | 149 | 5,716 |
| Commons-compress [4] | 1,585 | 37 | 263 | 29,249 |
| Commons-math [5] | 2,723 | 101 | 196 | 65,530 |
| Gson [8] | 1,348 | 293 | 788 | 21,416 |
| Jfreechart [10] | 2,291 | 148 | 324 | 40,354 |
| Jsoup [11] | 868 | 215 | 655 | 12,145 |
| Total | 9,149 | 879 | 2,375 | 174,510 |

for each smell in the test, we set up a checkpoint that asks whether the refactored test still exhibits the given issue. If the issue persists, the LLM continues refining the refactoring to eliminate the smell. For tests with multiple smells, we construct a chain of smell checkpoints, as illustrated in Figure 2. In the case of the test containing four smells, we collect the corresponding four checkpoints and integrate them into the prompt. The LLM uses this list to systematically check whether the smells have been fully removed. If any issues remain, the LLM will further adjust its refactoring until the test is completely free of the identified smells. This checkpoint mechanism ensures that even in complex cases with multiple smells, the LLM can perform thorough and effective refactoring, ultimately leading to higher-quality test code.

3.3.3 Refactoring Test Generation. It is essential for developers or testers to understand which tests have been refactored and the reasons behind these changes. To address this, we generate a detailed test refactoring report in this step. This report includes a list of refactored tests, specifying the file locations and test method names. It also outlines the detected smells for each test and the corresponding refactoring methods applied. Additionally, to facilitate subsequent testing and compilation, we organize the refactored test files and functions according to the original project's test structure.

4 EVALUATION

Our experiments are designed to address the following research questions:

- **RQ1: How is the quality of the test code after the refactoring of UTREFACTOR?**
- **RQ2: How effective is the refactoring of UTREFACTOR?**
- **RQ3: How effective is UTREFACTOR in eliminating each category of Test Smell?**
- **RQ4: What is the time efficiency of UTREFACTOR in test refactoring?**

4.1 Experimental Setup

Dataset. We collect projects from GitHub, including those from well-known organizations (e.g., Apache [1]) and popular projects (e.g., Jsoup [11] with 10.9k stars). To facilitate the test refactoring process, we set the following criteria for collection: first, to simplify test smell detection and make refactoring easier to validate, we collect projects written in Java and managed by Maven. Second, the source code of the project must compile successfully, and all unit tests are required to pass. Finally, each project must exhibit at least 100 test smells as detected by the *tsDetect* [15]. Ultimately, we select six open-source projects for our test refactoring experiments. As shown in Table 2, UTREFACTOR's integrated tool *tsDetect* identifies 879 unit tests with smells across these projects, with a combined total of 2,375 test smells detected.

Baselines. For the baseline comparison of refactoring tools, we choose two tools for our unit test refactoring benchmarks. First, *TESTAXE* [22], a tool implemented using the Rascal [13] meta-programming language, primarily designed to automatically upgrade projects from *JUnit* 4 to *JUnit* 5 to automatically detect and eliminate test smells in Maven-managed Java projects. It is rule-based and leverages features in the *JUnit* 5 testing framework to remove test smells. Second, considering that large language models (LLMs) inherently have the capability to refactor test code, we employ a default open-source LLM (*Llama3-70B*) with a generic prompt as another comparison baseline. As depicted in Figure 7, we use a standard prompt template, which provides the *Llama3-70B* with the original test code and all detected test smell types. The LLM is then tasked with removing these smells and generating the refactored test code.

Role: You are a Java testing expert, and now you need to refactor the test code which contains bad test code smell.

User: Given the following Unit Test, and the Test Smells it contains, eliminate the smells present in this test without altering the original functionality and logic of the test, and provide the refactored test code.

Code and Smells: [Unit Test] [Test Smells]

Fig. 7. Prompt template for default LLM used to eliminate smell in tests.

4.2 RQ1: How is the quality of the test code after the refactoring of UTREFACTOR?

Since the test refactoring process must eliminate test smells without altering the original test functionality, we first verify the quality of the refactored test code to ensure effective refactoring. This includes checking for code errors and ensuring that the functionality remains unchanged. Specifically, we first assess the syntax correctness of the refactored test code. To achieve this, we calculate the compilation pass rate and test execution pass rate of all refactored tests, evaluating whether UTREFACTOR introduce any errors during the structural changes that lead to compilation or runtime failures. Next, to check whether the functionality of the refactored test code remained intact, we compare the line and branch coverage before and after refactoring for all tests that passed execution. If there are no changes in coverage, this indicate that the refactoring only adjust the code structure without modifying the underlying functionality.

Table 3 presents the quality of the refactored test code across all open-source projects. As shown, UTREFACTOR refactor 879 unit tests with identified test smells from six open-source projects. The #CPR column represents the compilation pass rate of the refactored tests. We manually compile all refactored tests and calculate that the average compilation pass rate is 95%, with the highest rate being 97% in the *Jsoup* project. #EPR represents the execution pass rate of the refactored tests. Similarly, we manually execute all refactored tests and calculate an average #EPR of 89%, with the highest rate reaching 92% in the *Gson* and *Jsoup* projects. This indicates that while the refactoring process did introduce some errors, it remains largely effective, with the overall results demonstrating a solid level of reliability.

We analyze the tests where UTREFACTOR introduces errors after refactoring. In the *Gson* project, *testStrictComments* contains three assertions (*assertStrictEqualError*) without descriptive information, resulting in the detection of a AR (Assertion Roulette) smell. During the refactoring process, UTREFACTOR generates descriptive messages for each of the three assertions. However, a parameter mismatch error occurs during compilation. Upon further analysis, we find that *assertStrictEqualError* is a built-in assertion in *Gson*, different from the standard *JUnit* assertions. This assertion only accepts two parameters: an exception describing the expected behavior and an *expectedLocation*

Table 3. Quality of refactored test code generated by UTREFACTOR (#RTests - number of tests after refactoring, #CPR - test compilation pass rate, #EPR - test execution pass rate).

| Project | #RTests | #CPR | #EPR | Line Coverage | Branch Coverage |
|------------------|--------------|------------|------------|----------------|-----------------|
| | | | | cov.(unchgd.) | cov.(unchgd.) |
| Commons-cli | 126 | 93% | 89% | 98% (✓) | 95% (✓) |
| Commons-compress | 65 | 92% | 83% | 84% (✓) | 75% (✓) |
| Commons-math | 144 | 95% | 88% | 92% (✓) | 85% (✓) |
| Gson | 469 | 94% | 92% | 87% (✓) | 85% (✓) |
| Jfreechart | 314 | 95% | 81% | 54% (✓) | 45% (✓) |
| Jsoup | 404 | 97% | 92% | 86% (✓) | 80% (✓) |
| Total | 1,522 | 95% | 89% | 77% (✓) | 67% (✓) |

parameter. It does not support an additional message parameter. This conflicts with UTREFACTOR’s DSL rule for refactoring AR smells, which requires assertions to include a message parameter, leading to a compilation error and causing the smell to remain.

We calculate the coverage of tests that still pass after refactoring by using the *Jacoco* [9] test coverage tool in each project. As shown in Table 3, we observe that UTREFACTOR does not alter the original line coverage or branch coverage of the tests after refactoring. This indicates that UTREFACTOR only restructures the code, such as refactoring assertions or breaking down test methods, without changing the original functionality. It avoids introducing new calls to the project’s production APIs or omitting existing conditions or function calls within the tests. This outcome aligns with our expectations, as the goal of UTREFACTOR is to eliminate test smells and improve test code quality, rather than modifying the underlying functionality.

4.3 RQ2: How effective is the refactoring of UTREFACTOR?

We are next interested in evaluating the extent to which UTREFACTOR eliminates bad smells in refactored test code that still passes execution, thus validating the effectiveness of UTREFACTOR in test refactoring. Additionally, we compare and analyze UTREFACTOR’s effectiveness against two baseline tools. To assess refactoring effectiveness, we focus on two key metrics in this research question (RQ): the number of passing tests after refactoring and the number of remaining smells in those tests. We also measure the change in the total number of smells before and after refactoring, the greater the reduction rate, the more effective the automatic refactoring is in reducing overall test smells in the project. Table 4 shows the effectiveness of UTREFACTOR and the two baseline tools in refactoring tests across six Java open-source projects. Out of the 2,375 test smells present across the six projects, UTREFACTOR reduced the number to 265 after refactoring, achieving an average reduction rate of 89%. The *Commons-compress* project shows the highest reduction rate, reaching 94%. This demonstrates that UTREFACTOR is highly effective in reducing test smells. In particular, for the most prevalent smell, AR (Assertion Roulette), UTREFACTOR had the most significant impact, completely eliminating this smell by successfully adding descriptive messages to all assertions that lacked them. The effectiveness of UTREFACTOR in addressing different types of test smells will be discussed further in RQ3.

Comparison with TESTAXE. As shown in Table 4, TESTAXE achieves a 19% smell reduction rate in the *Commons-math* project, while in the *Commons-compress* and *Jsoup* projects, the reduction rate is less than 1%. In the *Commons-cli*, *Gson*, and *Jfreechart* projects, TESTAXE fails to eliminate any test smells. TESTAXE primarily aims to upgrade projects from JUnit 4 to JUnit 5. During this process, it uses JUnit 5 features to refactor existing tests and eliminate test smells. TESTAXE

Table 4. Comparison Results of Test Smell Elimination Effectiveness(#TS Num - number of Test Smells).

| Project | #TS Num | UTREFACTOR | | Llama3-70B | | TESTAXE | |
|------------------|--------------|------------|--------------|--------------|--------------|--------------|-----------------|
| | | aft. | rate | aft. | rate | aft. | rate |
| Commons-cli | 149 | 21 | ↓ 86% | 94 | ↓ 37% | - | - |
| Commons-compress | 263 | 16 | ↓ 94% | 55 | ↓ 79% | 261 | ↓ <1% |
| Commons-math | 196 | 28 | ↓ 86% | 107 | ↓ 45% | 158 | ↓ 19% |
| Gson | 788 | 87 | ↓ 89% | 375 | ↓ 52% | - | - |
| Jfreechart | 324 | 44 | ↓ 86% | 197 | ↓ 39% | - | - |
| Jsoup | 655 | 69 | ↓ 91% | 252 | ↓ 62% | 635 | ↓ <1% |
| Total | 2,375 | 69 | ↓ 89% | 1,080 | ↓ 55% | 2,315 | ↓ <1% |

relies on a set of built-in syntax matching and replacement rules for test refactoring. However, it includes only five rules related to smell elimination, limiting its effectiveness. For example, it cannot handle AR (Assertion Roulette), one of the most common test smells. Additionally, *TESTAXE*'s replacement rules require strict matching with the original test code, meaning that any code not covered by these rules remains unchanged. The biggest limitation of their approach is its poor adaptability. For example, in handling ECT (Exception Catching Throwing) smells, *TESTAXE* uses the `ExpectedExceptionTransformation` rule, which only matches patterns like `throws` in function signatures. However, test cases often involve exceptions handled in `try-catch` blocks that require refactoring, and since *TESTAXE*'s rules do not cover these patterns, it cannot eliminate such exception smells. These limitations significantly reduce *TESTAXE*'s time efficiency in eliminating and refactoring test smells.

Comparison with *Llama3-70B*. It is evident that when only providing the test code and corresponding smell types to *Llama3-70B* for refactoring, it reduces a total of 1,080 smells across the six projects, with an average reduction rate of 55%. This is lower than that achieved by UTREFACTOR. This shows that while the LLM has the ability to refactor test smells, its effectiveness is limited. After manual inspection of the LLM-refactored tests, we find that it performs best in handling AR (Assertion Roulette) smells. In tests with AR smells, the LLM successfully adds descriptive messages to assertions that lack them, which is attributed to its inherent code understanding capabilities. However, it does not eliminate all AR smells. When multiple smells are present in a test, using the default prompt (as shown in Figure 6) often leads to incomplete smell elimination, leaving AR smells unresolved. This issue is mitigated in UTREFACTOR by using a checkpoint mechanism, which ensures that each smell is checked and eliminated after refactoring. For other types of smells, the default LLM's ability is also limited. For example, in handling exception-related smells, without the structured refactoring DSL rules designed in UTREFACTOR, the *Llama3-70B* often tends to simply replacing `throws` statements with `try-catch` blocks, which does not effectively remove the smell. Overall, the default LLM exhibits more randomness in test refactoring. This characteristic becomes more prominent when multiple smells are present in a single test, resulting in unpredictable refactoring outcomes. In contrast, UTREFACTOR, with its integration of external knowledge and structured refactoring rules, consistently delivers more effective and stable smell elimination.

4.4 RQ3: How effective is UTREFACTOR in eliminating each category of Test Smell?

In this research question, we focus on UTREFACTOR's ability to eliminate different types of test smells. To do this, we first detect and collect all types of test smells present in the six open-source projects. We then analyze how effectively UTREFACTOR removes these smells. As noted in RQ2,

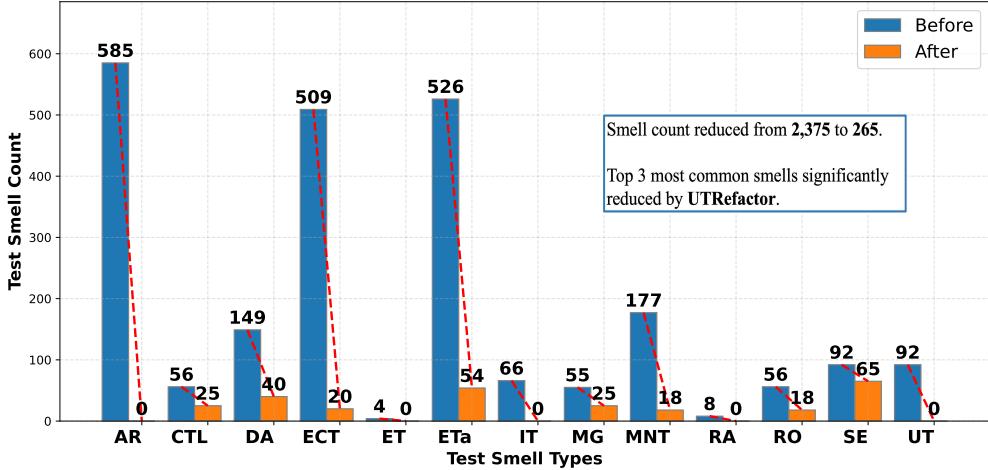


Fig. 8. Changes in the number of each type of test smell before and after test refactoring in UTREFACTOR (MG=Mystery Guest, RO=Resource Optimism, MNT=Magic Number Test, SE=Sensitive Equality, ETa=Eager Test, DA=Duplicate Assert, CTL=Conditional Test Logic, ECT=Exception Catching Throwing, AR=Assertion Roulette, RA=Redundant Assertion, IT=Ignored Test, UT=Unknown Test).

UTREFACTOR successfully reduces the total number of test smells from 2,375 to 265. Figure 8 provides detailed data on UTREFACTOR's ability to eliminate each type of test smell. From the figure, we observe that UTREFACTOR completely eliminates the most prevalent type, i.e., AR (Assertion Roulette) smell. This success is due to UTREFACTOR's integration of LLM code understanding capabilities, enabling it to infer appropriate descriptive messages based on the specific assert statements and surrounding code context. These messages help developers quickly identify the cause of errors when tests fail. Additionally, UTREFACTOR shows significant refactoring results for the two other high-frequency smells, ECT (Exception Catching Throwing) and ETa (Eager Test), reducing their numbers from 526 and 509 to 54 and 20, respectively.

We manually review the refactored tests generated by UTREFACTOR and analyze its effectiveness in eliminating each type of smell. Taking ETa (Eager Test) as an example, this smell occurs when a test includes assertions for multiple production functions, making the test's purpose unclear and violating the best practice of the single responsibility principle. The refactoring approach for this smell is to split the test based on the production functions it verifies. UTREFACTOR's advantage in eliminating ETa is demonstrated in two ways. First, its ETa DSL clearly defines how to identify API assertions, split the test, and generate new test methods. Second, with the help of LLM, UTREFACTOR can understand and reason based on context, effectively handling complex code structures while avoiding the randomness typically associated with LLM-generated tests.

For the cases where smell elimination failed, we conduct a manual review and analysis. From the Figure 8, we observe that UTREFACTOR's ability to handle certain less frequent smells is somewhat limited. A notable example is SE (Sensitive Equality), which occurs when the default `toString` method is used in assertions. The refactoring approach for this smell requires either the project to have overridden the `toString` method or to provide an equivalent method for object comparison. In other words, if the project neither overrides `toString` nor offers a functionally equivalent method, UTREFACTOR is unable to remove this type of smell. Overall, across the six open-source projects, UTREFACTOR shows less effectiveness in addressing this smell type, primarily due to the lack of overridden `toString` methods or alternative methods in the project.

4.5 RQ4: What is the time efficiency of UTREFACTOR in test refactoring?

In this research question, we focus on the time efficiency of UTREFACTOR during the test refactoring process. We first collect the time data for each step of UTREFACTOR and then compare the total time with the two baseline tools. Table 5 illustrates the time spent by UTREFACTOR at each refactoring step. Across all six open-source projects, the total time from detecting test smells to refactoring the 879 tests with identified smells is 4,379 seconds, averaging 3.8 seconds per test. This highlights UTREFACTOR's efficiency in terms of time consumption. Moreover, to accommodate various real-world refactoring scenarios, such as automatically refactoring test smells immediately after developers write a test or refactoring the entire test code of an existing project, UTREFACTOR supports refactoring at different levels: a single test, a single test file, or all test files within a project.

Table 5. Time consuming(s) for each step of refactoring tests in UTREFACTOR.

| Project | Step1 | Step2 | Step3 |
|--------------|-----------------|-------------------|-------------------|
| Cli | 24 | 4 | 221 |
| Compress | 69 | 3 | 101 |
| Math | 258 | 6 | 235 |
| Gson | 64 | 4 | 988 |
| Jfreechart | 90 | 5 | 697 |
| Jsoup | 31 | 2 | 1,127 |
| Total | 536(12%) | 24(<1%) | 3,369(87%) |

is a one-time process. Once this external information is built, it can be quickly accessed and loaded during the refactoring process, significantly reducing time consumption at this step.

Additionally, we compare the time consumption of UTREFACTOR with the two baselines, as shown in Figure 9. The most time-efficient tool is *TESTAXE*, which takes 600 seconds, followed by *Llama3-70B* with a total of 3,291 seconds. *TESTAXE* is rule-based, and its refactoring process involves parsing the source code into an abstract syntax tree (AST), performing nine types of operations such as node insertion, replacement, and deletion during tree traversal, and finally converting the updated AST back into test code. Since this process does not involve network API calls and the scope of its refactoring rules is limited, it has a relative advantage in terms of time efficiency. *Llama3-70B*, similar to UTREFACTOR, requires network calls during the refactoring process. However, *Llama3-70B* does not involve preprocessing the tests or loading external knowledge, which results in slightly lower time consumption compared to UTREFACTOR.

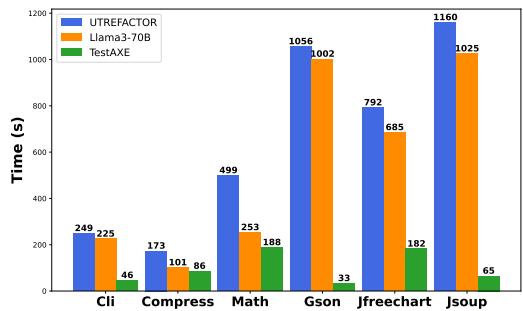


Fig. 9. Comparison of time consumption between UTREFACTOR and two baseline tools across each project.

5 DISCUSSION

5.1 Strengths of UTREFACTOR

In UTREFACTOR, we explore how LLMs perform automatic test refactoring tasks, guided by rules described in DSLs. This approach simulates the process that developers or testers follow during refactoring, from understanding the test's intent and identifying test smells to following step-by-step instructions outlined in the DSL. Compared to directly using an LLM for test refactoring, UTREFACTOR significantly reduces the risk of random errors caused by hallucinations, which can make the refactoring process unpredictable. Moreover, if developers directly use an LLM to refactor tests, in addition to the limitations mentioned earlier, there is often incomplete test smell elimination, requiring further manual intervention. In contrast, UTREFACTOR's checkpoint mechanism ensures a more thorough refactoring process, especially when multiple test smells are present, greatly reducing the need for manual involvement and lowering associated costs.

5.2 Integration of UTREFACTOR with LLMs

Closed-source LLMs often come with high token usage costs, and their large parameter sizes lead to significant deployment expenses. To address this, UTREFACTOR uses the open-source and free *Llama3-70B* model. However, considering the tool's extensibility, UTREFACTOR also supports replacing *Llama3-70B* with other LLM models. *ChatGPT* [2] is a widely recognized model and the current stable version *GPT-4o* [7]. We design an experiment to demonstrate that UTREFACTOR effectively eliminates test smells using alternative LLM models. As shown in Table 6, we compare two setups: one using the default *GPT-4o* with the general prompt (as illustrated in Figure 7) and another using UTREFACTOR with *Llama3-70B* replaced by *GPT-4o*. We randomly select 100 tests with smells from six open-source datasets, containing a total of 251 test smells. After refactoring the tests, Table 6 shows that using *GPT-4o* with the default prompt achieves a smell reduction rate of 55%, whereas UTREFACTOR achieves a reduction rate of 91%.

Table 6. Effectiveness of UTREFACTOR integrated with *GPT-4o* in eliminating test smells.

| Tool | #TS Num | aft.(rate) |
|------------------------------|---------|------------|
| Default <i>GPT-4o</i> | 251 | 108 (↓57%) |
| UTREFACTOR (<i>GPT-4o</i>) | 251 | 23 (↓91%) |

We manually review the test refactoring results using *GPT-4o*. Without guidance from external knowledge on test smells, the default *GPT-4o* encounters issues in eliminating smells. For example, in the *testFindRangeBounds* of the *jfreechart*, where four types of smells are present. *GPT-4o* removes only three smells but fails to eliminate the most common smell, *Assertion Roulette*. In other cases, we observe that

GPT-4o attempts to address *Assertion Roulette* by adding comments to assertion statements instead of explicitly adding a message, which does not properly resolve the smell. In contrast, UTREFACTOR leverages its DSL to clearly instruct the addition of a message to assertions and ensure that all smells are addressed during refactoring, avoiding the issues caused by the default LLM approach. In another example, the *testDrawWithNullInfo* contains a complex try/catch structure detected as *Exception Catching Throwing*. *GPT-4o* simply removes this block and adds an explicit throw in the method signature, but this fails to eliminate the smell. By contrast, guided by UTREFACTOR's DSL, the tool uses *assertNotThrow* to replace the try/catch block and successfully resolves the smell. This demonstrates that UTREFACTOR effectively eliminates smells even when using other LLMs like *GPT-4o*.

5.3 Threats to Validity

Threats to internal validity. To minimize hallucinations and reduce errors during the test smell elimination process, we provide LLMs with sufficient context related to test refactoring and design a refactoring DSL to guide the LLM step by step in removing test smells. However, the DSL in UTREFACTOR may not cover every possible scenario, which can impact the overall effectiveness of the test refactoring. Our refactoring DSL is designed as a flexible, external configuration file, making it easy to extend. For example, new smell types can be addressed by simply adding or updating DSL files, modifying refactoring steps to accommodate a broader range of scenarios.

Threats to external validity. We integrate the *tsDetect* tool into our process for test smell detection. This tool uses a built-in Java parser to analyze test code and identify smells, currently supporting Java versions up to 13. For incompatible Java versions, *tsDetect* may encounter syntax parsing errors during detection, which could prevent the identification of test smells, thus impacting the effectiveness of smell elimination. Given that test smell detection tools are continually evolving, UTREFACTOR is designed to be highly extensible, allowing for the replacement of the built-in test smell detection tool. When encountering incompatible Java versions, a more robust detection tool can be integrated to address undetected smells, thereby improving the overall performance of the test refactoring process.

6 RELATED WORK

The Impact and Refactoring of Test Smells. Several studies [19, 20, 25, 26, 28, 31, 32, 34–36] have focused on the impact of test smells, including how they affect the development process, software maintenance, and comprehension. To investigate how much developers acknowledge the presence of test smells, Soares et al. [35] conducted a study with 73 experienced open-source developers across 272 projects. They analyzed preferences and motivations related to 10 identified test smells by comparing the original and refactored versions of test code. The results showed that 78% of developers acknowledged the negative impact of test smells and preferred refactored tests. Besides, they explored the use of new JUnit 5 features to eliminate and prevent test smells in another study [36]. In an empirical study on 485 popular Java open-source projects from GitHub, Soares et al. found that only 15.9% of projects used the JUnit 5 library. By applying seven JUnit 5 features to address test smells, they conducted a survey of 212 developers and submitted 38 pull requests, achieving a 94% acceptance rate among respondents.

Test Smell Detection. There are many research methods and tools [17, 18, 21, 24, 29, 30, 33, 37–39] available for detecting test smells across different programming languages. Palomba et al. [29] developed *TASTE*, an automated textual-based tool for detecting several types of test smells. Compared to previous structure-based detection methods, this tool improved smell detection effectiveness by 44%. Peruma et al. [30] recently developed a tool called *tsDetect*, capable of detecting 19 test smells in Java. It used a set of detection rules to locate existing test smells in test code. Wang et al. [38] proposed a tool called *PYNODE*, designed to detect 17 types of test smells within Python’s standard *Unittest* framework, and introduced a new test smell type called *Suboptimal Assert*. *PYNODE* was available as a plugin for *PyCharm*, and in an empirical study conducted across 248 Python projects, they found that 98% of projects contained at least one type of test smell. Unlike work focused on test smell detection, our research aims to explore how the latest large language models could improve the performance of eliminating detected smells.

7 CONCLUSION AND FUTURE WORK

This paper introduces UTREFACTOR, a tool that focuses on the automatic detection and refactoring of test smells. In this work, we explore how leveraging refactoring DSLs and incorporating test context

knowledge optimize and enhance the ability of open-source LLMs to automatically refactor test code. UTREFACTOR supports multiple test smell types and eliminates smells at varying granularities. Compared to existing methods, UTREFACTOR demonstrates greater effectiveness in eliminating various types of test smells from code. In the future, we plan to extend our refactoring rules to support additional programming languages, such as Python and C/C++. Additionally, we intend to investigate the impact of using different LLM sizes and parameters on the test refactoring process.

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