Characterizing Virtual Reality Software Testing

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Abstract—Virtual Reality (VR) is an emerging technique that provides a unique real-time experience for users. VR technologies have provided revolutionary user experiences in various scenarios (e.g., training, education, product/architecture design, gaming, remote conference/tour, etc.). However, testing VR applications is challenging due to their nature which necessitates physical interactivity, and their reliance on hardware systems. Despite the recent advancements in VR technology and its usage scenarios, we still know little about VR application testing. To fill up this knowledge gap, we performed an empirical study on 97 open-source VR applications including 28 industrial projects. Our analysis identified that 74.2% of the VR projects evaluated did not have any tests, and for the VR projects that did, the median functional-method to test-method ratio was low in comparison to other project categories. Moreover, we uncovered tool support issues concerning the measurement of VR code coverage, and the code coverage and assertion density results we were able to generate were also relatively low, as they respectively had averages of 15.63% and 17.69%. Finally, through manual analysis of 220 test cases from four VR applications and 281 test cases from four non-VR applications, we identified that VR applications require specific categories of test cases to ensure VR application quality attributes. We believe that our findings constitute a call to action for the VR development community to improve testing aspects and provide directions for software engineering researchers to develop advanced techniques for automatic test case generation and test quality analysis for VR applications.

I. INTRODUCTION

Virtual Reality (VR) applications provide an immersive experience to end-users with a computer-generated environment that includes scenes and objects that appear real in their surroundings. Although the term virtual reality was introduced three decades ago [1], its real surge started around 2016, with the release of VR devices such as Oculus Rift [2] and HTC Vive [3], and software support from the likes of Unity and Unreal Engine. Indeed, both industrial and personal usage have surged in recent years. According to a 2021 study [4], the global virtual reality market exhibited a significant growth of 42.3% in 2020 compared to the years 2017-2019, and this market is projected to reach over $80 billion within the next seven years. To accurately simulate the user experience and to support areas such as education, product/architecture design, remote conferencing/touring, and surgical procedures, high-quality VR software is essential. However, existing automated techniques’ support for VR software development is still at an early stage with few available tools and frameworks, especially for VR testing.

The importance of software testing and quality assurance has been widely affirmed in both academic and industrial communities. To address the challenges and design the appropriate solutions, researchers have carried out many testing-practices studies with different approaches including human-developers-oriented interviews [5] and large-scaled quantitative and qualitative empirical studies [6], [7]. Moreover, test-practice investigations have been reported for different application types: mobile applications [8], [9], Machine learning applications [10], and many more [11], [12], [13], [14], [15]. Testing VR applications is a challenging task [16], [17], [18] due to the complex design of VR projects, the user-immersive experience, and inadequate technical support for VR development, debugging, and testing activities. So far, existing VR research activities have focused on development support, such as performance optimization [19], code dependency [20], and code smell detection [21]. In addition, there are several studies on Game applications, such as regression testing for Games [22], and a differentiation study between Game and Non-Game applications [23]. However, none of the existing works studied the prevalence, effectiveness, design quality, and characteristics of VR software testing. To remedy this knowledge gap, we opted to perform a qualitative and quantitative analysis of the existing testing practices in VR applications. We carried out an empirical study on 97 VR applications in this paper, ranging from small-scale projects to projects backed by large companies and organizations like Microsoft and Unity Technologies, where we analyzed the prevalence, quality, and effectiveness of existing VR tests. Then, we categorized the different VR tests into different types based on their characteristics. Finally, we analyzed the tests of four hand-picked non-VR projects to determine which of the aforementioned test categories were VR-specific.

Our main research questions are:

- **RQ1**: To What Extent Are Test Cases Developed for VR Applications?

**Motivation.** This question allowed us to estimate the current effort that VR developers put into testing their projects and understand the potential need for VR testing support.

**Answer.** We discovered test cases in only 25 out of the
97 VR projects we analyzed. Moreover, we found that the current ratio of code-to-test is too low using both class and method granularities, especially as they were more than 26 times lower than those found by Vidacs et al. [24] who performed a similar analysis on test-to-code ratios. We believe these results indicate an important need for improved testing support.

- **RQ2**: How effective are the test cases developed in VR applications?
  **Motivation.** To develop a deeper understanding of the status quo of VR testing, we adopted two state-of-the-art metrics to evaluate the effectiveness of the existing test methods: code coverage and assertion density.
  **Answer.** For code coverage, within the 7 measurable projects, the average rate was more than 5 times lower than the recommended rate of 80% [25], [26], and the assertion density has values that are lower than the recommended rates, and which are linked to higher bug rates within software projects [27]. These findings indicate that the testing practices of VR projects are less effective.

- **RQ3**: What is the design quality of test cases developed for VR applications?
  **Motivation.** The metrics we used in RQ2 do not reflect the design quality of test methods. With this question, we wanted to evaluate the quality of existing tests, and we believe these findings can help guide future testing tool design.
  **Answer.** Using the work of De Bleser et al. [28] as a guide, we analyzed the tests for 6 smell types. We found that on average 38.43% of a project’s tests have at least 1 smell type, and a project can have as much as 92% smelly tests. This indicates that test smells are common within most VR test methods, resulting in a lower design quality.

- **RQ4**: What are the different categories of VR Test Cases and which categories are specific to VR?
  **Motivation.** With this question, we aimed to discover testing scenarios that reflect characteristics of VR applications. VR applications differ from other application types because of their specific-hardware support, new user experiences, and unique immersive design, among other characteristics. Similar to Muccini et al.’s work [29] which examined the differences between mobile and traditional applications, we aim to fill a similar knowledge gap and provide insight for future VR testing design.
  **Answer.** In our study, we manually analyzed 220 test methods from 4 VR projects that had at least a 10% code coverage. In total, we defined 10 main testing categories, such as Physics Test, Animation Test, Graphics Test, Asset Test, etc., which are detailed within Section IV-D. To further understand which categories are specific to VR projects, we followed the same methodology and analyzed 281 test methods from four non-VR projects that meet the same code coverage criteria. We found four main categories and four subcategories of two main categories were not present in any of these non-VR test methods.

The contributions of this paper are:

- The first quantitative and qualitative study on existing test practices of VR applications
- The first tool for test effectiveness analysis and test smell identification for Unity-based projects.
- A detailed test case effectiveness analysis via the test coverage and assertion density metrics, and detailed test-quality analysis through the test-smell detection.
- A taxonomy containing 10 main test categories which reflect the characteristics of the VR applications, as well as the identification of VR-specific categories within this taxonomy.

This paper is organized as follows: Section II presents the background that defines terms we later use in our manual analysis; Section III contains details about the dataset and the methodology used within our automated and manual analysis; Section IV describes the evaluation which answers all four research questions, followed by threats to validity in Section V. Section VI includes related work; Section VII describes the implications of this paper and we conclude the work in Section VIII.

## II. Background

Automatic software testing allows developers to test application code in an automated, rapid, and reliable way. Similar to traditional software applications, automated software testing can also be applied to VR applications. In this study, we analyzed the test characteristics of 97 Unity-based VR applications collected from UnityList [30], since Unity is one of the most popular frameworks for developing VR applications [31]. VR tests mainly focus on the behavior of VR subsystems and class components. While analyzing VR tests, familiarity with how Unity works and some terms is required.

**Physics System:** ensures that the virtual objects correctly respond to different forces such as collisions and gravity. Unity platform provides RigidBody APIs to enable the physics engine control of objects. Collision and Colliding are also important concepts in VR projects that define how virtual objects react to overlapping with or without physical effects.

**Graphics System:** enables developers to control the appearance of VR applications. This includes Rendering, Display, Camera, Lighting, etc. In 3-D graphic design, rendering is the process of adding shading, color, and lamination to a 2-D or 3-D wireframe in order to create life-like images on a screen. This process can be preloaded or occur in real time when users interact with VR applications. Display is related to displaying the rendered objects within the VR scene, which users can view through hardware such as monitors or head-mounted devices. Unlike non-VR applications, VR applications can create multiple cameras in the same scene, and the display will update along with the camera switching and location changing. The camera represents the view angle that the user utilizes to see the virtual world.

**Animation System:** allows developers to animate target objects via jumping, moving, stopping, rotating, etc. The animation design in VR applications is more complicated than that of non-VR applications. With fixed angles in non-VR applications, animation design is a linear process that focuses on the representation from a locked direction or view.
However, in VR applications, animating user surroundings is a parallelized process. Developers need to ensure the correctness of the representation from any arbitrary angle.

Other terms: GameObject: the fundamental class for all the objects in a virtual world. By combining the different controls and features, developers can realize customized functions like moving objects. Colliders represent the invisible physical shapes of objects. The Physics system uses them to decide the physical effect like overlapping between objects.

III. RESEARCH APPROACH

Fig. 1: Overview of Research Approach

The research approach overview is illustrated within Figure 1. In this section, we will first introduce the studied dataset, then describe the AST-based automatic analyses used to measure the test prevalence, efficiency, and quality, and eventually discuss the manual analysis used to discover the taxonomy of VR tests as well as identify VR-only test categories.

A. Dataset

Within this work, we wanted to study a group of Open Source Unity-based Virtual Reality software projects. Since collecting a dataset can be a time-consuming process and is not a goal of this study, we opted to use the dataset of Nusrat et al. [19], containing 100 VR projects which are Unity-based. We specifically chose this dataset as it contains manually-verified VR projects from Unity, one of the most popular Game and VR development engines [31]. We were unable to obtain 3 projects due to de-listing. We identified the different versions of Unity used in the development of the projects we obtained: 3 projects were using Unity 2021, 1 project was using Unity 2020, 18 projects were using Unity 2019, 24 projects were using Unity 2018, 23 projects were using Unity 2017, 27 projects were using Unity 5, 1 projects was using Unity 4. This diversity of VR projects should allow us to uncover knowledge about testing practices and tool support across various generations of the Unity framework. Furthermore, while the majority of the projects we considered were independent and academic projects, respectively 55 and 14 projects, it also contained 28 industrial projects backed by the companies and organizations like Microsoft, Unity Technologies, and Vive. All VR projects contain a minimum of 100 commits, with average and median commits of 728.42 and 204, respectively. Furthermore, they are composed of teams ranging from 1 person to 1568 people, with an average of 61.28 and a median of 4 people.

In order to be able to compare and contrast the types of tests used within non-VR projects and those used within our set of VR projects, we manually collected four Unity-based non-VR projects, based on similar criteria to those used by Nusrat et al., and verified that they had a code coverage of at least 10%, similar to that of the four VR projects we selected for the manual analysis and test taxonomy construction, which are detailed within Section III-C. The four VR projects we selected for manual analysis were composed of two Game and two Tool projects. To take into account of characteristics these two project types during our comparative analysis, we selected two non-VR Game projects, and two non-VR Tool projects for our non-VR comparison set.

B. Methodology of Automatic Analysis

1) Static Analysis of Unity Projects: Since Unity makes use of the standard .Net Framework, alongside its internal frameworks and classes, and the C# programming language for its scripting [32], we needed to use an AST generator that supported these technologies. We opted to use SrcML [33] to generate the ASTs of the Unity C# code. SrcML is a research tool that allows the generation of ASTs for various programming languages, which facilitates the extension of our approach and tools to other sets of projects that use different programming languages. It supports C#, and does not rely on compilation to generate ASTs, thus allowing us to avoid any compatibility problems. For each VR project within our dataset, we analyzed its repository to extract the C# code files and then generated the AST of each file to perform the different analyses described in the following sections.

2) VR Test Cases Prevalence: In order to evaluate the prevalence of test cases within our set of VR projects, We counted the number of the test methods and the test classes, in addition to the number of functional methods and classes of our VR projects. Using these data points, we calculated the following metrics for each project:

\[
TestToCodeMethodRatio = \frac{Count(TestMethods)}{Count(FuncMethods)}
\]

\[
TestToCodeClassRatio = \frac{Count(TestClasses)}{Count(FuncClasses)}
\]

Based on the work of Klammer et al. [34] and Williams et al. [35], these metrics adequately represent the relative frequency of test code within our VR projects.

3) VR Test Cases Effectiveness: A practical way of measuring the effectiveness of tests in a software project is to calculate the Code Coverage [36], which denotes the degree to which the functional code is executed after a test suite finishes running. It is calculated via the ratio of the LOCs of functional code executed when tests are run to the total amount of coverable code within a project. This metric has been used by Pecorelli et al. in the context of Open-source Android apps [6]. Ivanković et al. in the context of software projects at Google [37], and Kochhar et al. also applied it to OSS projects [38]. The equation of code coverage is shown below:

\[
Coverage\text{Percentage} = \frac{\text{Func\text{LOCs}\text{ExecutedWhenTestsRun}}}{\text{CoverableFunc\text{LOCs}}}
\]
The generation of this metric and coverage reports is only possible through the use of Unity 2019.3 or newer [39], making it obligatory to upgrade the projects using an older version of Unity to at least that version in order to generate code coverage metrics. We planned to directly generate code coverage reports for 16 projects without upgrading and indirectly generate the code coverage reports for the rest of the projects with tests after upgrading them to Unity 2019.3 or newer. However, out of the 25 projects that we detected had tests via our automatic method, only 13 had tests runnable via Unity. In addition, we were only able to generate code coverage reports for 7 out of these 13 projects. Among the projects for which we were unable to generate coverage reports, addyi@SoftwareCity and RussellXie7@Unity_Hololens_Dev, were using Unity 5, and their tests were no longer runnable via Unity when they were updated to Unity 2017 or newer. Three projects had various compilation problems. Finally, Microsoft@MixedRealityToolKit-Unity, runs the coverage tool but its report is not generated.

To further clarify our findings regarding the effectiveness of the tests from our VR project set and circumvent some of the issues we encountered for code coverage report generation, we opted to use the Assertion Density [27], [40] metric to evaluate the test cases. This metric is calculated via the ratio of the number of assertions to the length of test cases that contain them. This metric's equation is:

\[
\text{AssertionDensity} = \frac{\text{NbAssertions}}{\text{TestLOCs}}
\]

4) VR Test cases Design Quality: In order to evaluate the quality of the test cases within our project set, we scanned them for Test smells [41], [42], [43]. They are similar to regular code smells in being symptomatic of technical debt and predicting future problems, but they are specific to test code. We considered six test smells from the work of De Bleser et al. [28], as they were found to be the most prevalent in a collection of previous works [44], [44], [45], and adapted them to the context of VR applications. These smells are:

**Assertion Roulette (AR):** If a test case contains more than one assertion, at least one of which does not provide a message when detecting a failure, it can be hard to diagnose which problems are present within the functional code being tested.

**General Fixture (GF):** A test fixture is too general if it initializes fields that are not used by one or more test methods, making it difficult to discern which fields are being shared by the different test methods within a test class.

**Sensitive Equality (SE):** If a test case has an assertion that compares the state of objects by comparing their representations as text, for example by using their ToString() methods, it makes itself susceptible to errors due to irrelevant textual representation details such as spaces.

**Eager Test (ET):** We consider a test that evaluates more than one functional method with the same fixture Eager. This smell violates the principle that every test case should only test one method, and the test failure should only signify issues within that method, not another irrelevant method.

**Lazy Test (LT):** A test case is lazy if it tests the same functional method using the same fixture as another test method. The problem this smell implies is that after modifying one function that is being tested, multiple test methods need to be updated accordingly. Thus this smell will affect the maintainability of test cases.

**Mystery Guest (MG):** A test case has this smell if it uses external resources that are not managed by a fixture or are not Mock objects. This smell may cause issues since external resources might change over time or be unavailable during test-case execution. For example, a test method can fail if a specific database (sqlite object) or file object are not available during its execution.

5) Evaluation of smell-detection tool: To evaluate the accuracy of our smell-detection tool and verify the correctness of our findings, we first applied the automated approach to four VR projects from the dataset with a coverage rate above 10%. Then two co-authors manually evaluated the same projects separately by labeling the test methods with any corresponding smell types. Both co-authors found 220 test methods, which is the same number found by the tool. An average Kappa of 0.92 was found between the authors across the different smell types, signaling high agreement, and any differences were then resolved via discussion. Upon evaluating the automatically detected smells using the manual observations as a baseline, on average, an accuracy of 91.35%, a recall of 92.62%, and an F-1 score of 91.98% were found across the aforementioned test smell categories. As noted in Section IV-C, no instances of Lazy Test and Sensitive Equality were found via the manual or automatic analyses we performed. To verify the correctness of our tool for these smells, we developed one test stub for the sensitive equality smell and two test stubs for the Lazy test smell and verified that our tool correctly detects these smells.

C. Methodology of Manual Analysis

To explore the characteristics of VR test cases and understand the differences between VR software testing and non-VR software testing, we carried out a manual analysis with a focus on discovering unique testing scenarios, exploring the test design patterns, and testing goals. Based on the automatic results within Section IV-B, we ranked all the VR projects with executable test methods by their code coverage and selected the ones with at least 10% coverage. We believe this selection allows us to select projects which have relatively more effective test methods than others. Eventually, we chose four projects, composed of two Tool and two Game projects, and which included 220 test methods.

There were no existing categories for authors to use as a reference when this study was conducted. Since we had to start from scratch in our categorization of the VR test types, we designed our manual approaches to minimize bias. First, two co-authors separately observed all the test methods and their related source code, and also performed an exploration of Unity documentation and VR developers’ forums to generate a comprehensive report for every test method. This report included details such as Unity API calls, observed tested
target and environment behavior, test scenario description, text method code pattern, and corresponding tested functional code pattern. Then, we asked a third co-author with previous VR experience to join the process. We assume this author carries less bias in deciding the categorization of the VR test code designs which were uncovered in the earlier step, as this author did not participate in it. These three co-authors then categorized all 220 test methods separately by reviewing the observed records. Eventually, voting within three rounds of consensus meetings was carried out to finalize the results and resolve any disagreements. Before resolving the disagreements, Fleiss’ Kappa coefficient was calculated, and was more than 0.81, indicating a very good agreement between co-authors. A similar process of manual categorization and discussion was followed to classify the 281 non-VR test cases, extracted from the four non-VR projects, within the newly-created test taxonomy. The Fleiss’ Kappa coefficient for this process was 0.86, indicating very good agreement between co-authors as well.

IV. EMPIRICAL EVALUATION

A. To What Extent Are Test Cases Developed for VR Applications?

In order to identify the prevalence of test code in VR applications, we calculated the Method and Class ratios of test code in comparison to functional code for VR projects with test cases. The recommended practices indicate that the test code to functional lines of code ratio is 3:1, or in more general cases between 1:1 and 1:10 [46]. Indeed, it is recommended that test code be added in parallel to functional code, where one test class should evaluate one functional class, and one test method should evaluate on functional method. This suggests that when considering the Method and Class granularity of ratios, the ideal values are close to 1. However, the results illustrated in Figure 2 show that test code only represents a small portion of VR projects’ code and that current VR testing prevalence is far from the ideal scenario. Indeed, these Method and Class ratios are also significantly worse in comparison to other categories of software projects such as industrial Java projects, analyzed by Klammer et al. [34], where the equivalent LOC ratio was around 0.6 for the totality of the code-base, or C# projects by Microsoft [35], where the LOC ratio was between 0.35 and 0.89.

B. How effective are the test cases developed in VR applications?

As discussed within Section III-B3 generating code coverage on the majority of Unity projects has proven challenging. Furthermore, the code coverage results we were able to generate, illustrated within Figure 3, paint a grim picture of VR testing’s effectiveness. While there is no universal code coverage rate that all software projects should target, an 80% rate of code coverage is the general recommendation [25], [26]. Yet, the highest coverage rate we noted was 31.25%, the lowest was 1.29%, and the median was 15.28%, thus putting into doubt the effectiveness of the tests within the project for which we were able to measure the code coverage. Furthermore, the issues regarding the lack of code coverage detection for Unity versions below 2019.3, especially when combined with the plethora of problems associated with the process of updating Unity projects using older versions to this version, highlight the lacking tool support in Unity for testing-related activities. When considering the metric of Assertion density, also illustrated within Figure 3 for projects that had test cases, it is clear that these values are not more encouraging than those of Code Coverage. Indeed, the median value of 14.73% we found for this metric in VR applications is even lower than that found within mobile applications [8], and the values found for Assertion Density and Code Coverage are linked with less effective testing practices [47]. Overall, the results we found show a massive need for testing support for independent developers of VR projects.

C. What is the design quality of Test Cases Developed for VR Applications?

After evaluating the extensiveness and effectiveness of test cases developed within our project set, we analyzed them to evaluate their quality using the method outlined in Section III-B4 and we obtained the following results:

**Assertion Roulette (AR):** It is clear within Figure 4 that the AR smell is quite common within our set of VR projects. Indeed, 18% of the projects we analyzed had assertion roulette within 20% or more of their test cases.

Listing 1 is an example of an assertion roulette from the watson-developer-cloud@unity-sdk project, where the test is attempting to verify whether the feedback object meets the developer’s expectations. It would be difficult to
diagnose the exact cause of this test’s failures. For example, whether the feedback response is null, or whether it’s empty, as no messages are given in the assertion statements in lines 3 & 4.

Listing 1: Assertion Roulette Smell from unity-sdk

General Fixture(GF): The GF smell is quite widespread within our project set, as illustrated within Figure 4 and was found in 18% or more tests of 12 projects.

Listing 2: General Fixture Smell from vimeo-unity-sdk

Eager Test(ET): For the ET smell, represented within Figure 4 it is clear that this smell is also common within our VR project-set than the two previously-mentioned smells. Indeed, we found that 16 projects have this smell within 10% or more of their test cases.

Listing 3: Eager Test Smell from PlanetariaUnity

Lazy Test (LT) and Sensitive Equality(SE): We did not discover any examples of these smells within the manual inspection used to verify the accuracy of our smell-detecting tool. In the case of the SE smell, we found that most comparisons of objects within test cases were based on a specific object’s property. Since most objects did not override the default ToString method, it makes the evaluation for comparative purposes based on their textual representation of limited usefulness. Furthermore, based on the findings in Section IV-A, it’s clear that the developers of the VR project-set write much less test code than functional code, thus making it less likely that they would write multiple tests for the same method. In fact, the results we found regarding the ET smell earlier within this section point to the opposite practice of testing multiple functional code methods within the same test being the more common, if ill-advised, practice.

We contextualized the overall test smell detection results from VR projects by comparing them with those from a similar test smell study of open-source Android applications by Peruma et al. [9] While 54.86% of files analyzed in Android exhibited the Assertation Roulette smell, an average of 38.43% of tests within VR projects we analyzed possessed this smell. A similar trend is noted for the other smells as well, where Eager Test was found in 38.68% of Android projects’ tests, it was found on average within 20.52% of our VR projects’ tests. For Lazy Test, Sensitive Equality, and Mystery Guest smells, the three means were close to 0% for VR projects, and respectively were 29.50%, 9.19%, and 11.65% within Android projects. The only exception is General Fixture, which was found within 11.67% of Android projects’ tests and within an average of 33.72% of VR projects’ tests. Overall, both application types show a comparable and problematic
frequency of the different test smells. However, the situation in VR applications is considerably worse considering the lack of prevalence and effectiveness of its testing overall.

D. What are the different categories of VR Test Cases and which categories are specific to VR?

To understand the test types that reflect the characteristics of VR applications, we followed the methodology discussed in Section III-C and carried out a manual analysis of 220 test methods from four VR projects. We divided all the test methods into ten different main categories. Figure 5 represents the taxonomy that we have generated based on a parent-child hierarchy. The digits indicate the number of test cases we discovered for the corresponding category. In addition, we conducted a second manual analysis on the test cases of non-VR Unity Projects to identify the test categories that are unique to VR projects, indicated by stars within Figure 5. In the rest of this section, we will carefully discuss each of the test categories as well as their sub-categories by giving detailed definitions. We present code examples to help avoid the bias of definition descriptions, but these definitions can also be expanded to general cases in other VR frameworks.

1) Audio Test: Audio Test is the test that validates if the sound works correctly, such as playing, pausing, and stopping the sound clips. The sound design of VR projects is supposed to provide users with a believable experience. Rather than being separate from the environment and only coming from a single direction, sounds in a virtual world are designed to be more interactive. We found 10 test methods that fall into this category.

2) Physics Test: Physics Test ensures the physical interaction between objects is correctly represented in effects like collision, falling due to gravity, and other forces. The key concept of physics is to have one or more forces that apply to objects. Its subcategories are:

Rigidbody Property Test. Rigidbody is a component of GameObject that enables the Unity physics engine control. It allows interaction with real-time physics, which includes forces, gravity, mass, and momentum. The Rigidbody Property Test is primarily concerned with physical behaviors such as movement and rotation. We identified 19 of them in total.

Colliding Test. Colliding in VR represents an interaction between two or more objects that does not trigger the physical collision effect. Colliding can be divided into three stages: at the start of colliding, during colliding, and after colliding. Colliding Tests evaluate the correctness of this dynamic process.

Listing 5: Colliding Test from vr-pacman

```csharp
[UnityTest]
public IEnumerator CollidingWithTeleporterMovesPlayer()
{
    Vector3 positionBeforeTeleport = pacman.transform.position;
    // position;
    pacman.transform.position = teleporter.transform.position;
    yield return new WaitForSeconds(WAIT_TIME);
    Assert.AreEqual(positionBeforeTeleport, pacman.transform.position);
}
```

Listing 6: Animation Test from vr-pacman

```csharp
[UnityTest]
public IEnumerator ResetPositionsWork()
{
    Vector3 pacmanPos = pacman.transform.position;
    Vector3 ghostPos = ghost.transform.position;
    goManager.StartMovingEntities();
    yield return new WaitForSeconds(WAIT_TIME);
    goManager.StopMovingEntities();
    Assert.AreEqual(pacmanPos, pacman.transform.position);
    Assert.AreEqual(ghostPos, ghost.transform.position);
}
```

The test design we observed in the test cases follows the three previously-described stages. The test method will first record tested properties and targets before colliding. Then, it will trigger the colliding condition by updating the interaction between the objects. After waiting for a short system response time, the test method will collect the new value of the tested properties and targets. Eventually, an assertion will be carried out between old values and new values or between new values and expected values.

Listing 5 shows an example of a colliding test from the project iamtomhewitt@vr-pacman in the file Pacman-CollisionTests.cs. The test case first sets the initial position for GameObject pacman in line 3. Then, it makes pacman position overlap with the teleporter position in line 4 by assigning the same value to these two positions. The overlapping of two colliders then triggers the colliding handling event, which results in pacman position updating. Specifically, OnTriggerEnter method is called by Unity, and the corresponding x, y, and z values of pacman are updated by the value of teleporter. After a waiting time, an assertion is inserted at line 6 to check whether the new position is different from the initial position. In total, we identified 19 colliding test methods.

Collision Test. Collision is very similar to colliding in VR. The major difference is that a collision will trigger a physical collision effect. For example, when a car is driving toward a wall, colliding will let the vehicle pass through the wall without stopping, but a collision will result in a crash where the vehicle hits the wall and stops. Collision Tests verify the correctness of the expected functionalities in regards to the process of collision. Similar to colliding, collision also includes three stages: entering, during, and after the collision. We found 10 tests of this category.

3) GUI Test: GUI Tests make sure that visualized interface components such as text, layouts, and input fields in VR applications work as specified. In traditional software, all the visualized items can be categorized as GUI components. In VR applications, both the GUI and the scene can be visualized at the same time. The scene may be changed by the camera position but the GUI may remain the same. The one test example we found evaluates the conversion from numeric values to GUI text.

4) Animation Test: Animation Tests verify the correctness of the expected functionalities and properties when target objects are in action. For example, location updates, moving, stopping, and rotation. The test cases we observed all follow a time-order-oriented design, where an assertion is inserted to compare the status before and after time frame updates. Unity provides a PlayMode testing scheme that executes the test code dynamically when the VR application is running.
Listing 6 shows an example of an Animation Test from the project iamtomhewitt@vr-pacman in GameObjectManagerTest.cs. In lines 3 and 4, two GameObjects’ positions have been recorded into two 3-D vector objects. From lines 5 to 8, the goManager object commands all the objects in the scene to move, stop, and then reset. Then the Update APIs defined in all GameObjects will take the corresponding actions to update their positions frame by frame. Eventually, in lines 9 and 10, the test oracles are inserted to compare the positions value update. In total, we identified 19 Animation test methods.

5) Graphics Test: Graphics Test tests the appearance of VR application. It includes Camera, Rendering, Display, Lighting, etc. The following subcategories are based on the test cases observed.

Camera Property Test. In VR applications, developers design one or more cameras in the virtual environment to provide users with different aspects of an immersive experience. Depending on the viewport space point, which is a relative point to the camera (i.e., the field of view based on camera features like locations, rotations, and scale), objects will be rendered in the VR world by following different performance-optimization purposes. Based on these special features, Camera Property Tests involve camera functionalities, such as camera counting, camera moving, rendered objects checking, etc. We identified one method in total.

Listing 7 shows an example of a Camera Property Test from project iamtomhewitt@jet-dash-vr in the file PlayerControlTests.cs. This project has two preset cameras in the scene, VR Camera and a Normal Camera. In line 3, GameSettingsManager gs activates its VrMode by passing a boolean value true to SetVrMode. Next in line 4, PlayControl pc initializes the VR scene by invoking the Start method, where the viewport will be provided to users, as well as the corresponding audio listener and clip management. The final assertion in line 5 is to examine the existence of a Normal Camera with the tag “MainCamera”.

Listing 8: Display Property Test from MapboxARGame

Rendering Test. A VR world consists of multiple visible and invisible entities. The goal of rendering is to create these entities in a user’s field of view (camera view). To obtain a more realistic result, developers need to consider factors like texturing, lighting, image effects, etc. A rendering test checks the correctness of these processes. For example, in a VR map-based project, one of the tests may check if the tiles have been successfully loaded onto the scene. We found 2 tests belonging of this category.

6) Asset Test: An asset is any item that the developer uses to create the VR application. Assets include visual, audio, or other elements like models and textures. An asset can either be from outside of Unity as a file or inside of it as internal data from the editor. Asset Tests verify the assets during the importing, loading, unloading, distributing, and other processes. Correctly managing a large number of assets automatically is a demanding task for VR developers. We found 1 test of this category.

7) Network Test: Networking and multiplayer support are two features in VR applications that require local or wide-area network access. Network tests check whether network calls and responses are correct, such as response count and re-
sponse data. They ensure that the receiving end is configured correctly and that data is transmitted between the sender and the receiver without any issues. Testing a real-time multiplayer feature ensures that the connections between clients, servers, and hosts are working correctly. 10 Tests of this category were found.

8) **Data Test:** Data tests involve dataset evaluation through caching systems, local file systems, or other local and remote databases. These tests confirm that a VR application is storing, retrieving, deleting, and updating data appropriately. For example, testing whether multiple objects can be added to a cache system concurrently. Its subcategories are Caching Test, Concurrent Data Access Test, DB Access Test, and Player Pref Test. PlayerPref is a built-in Unity API that helps developers quickly access internal data between frames and across multiple VR scenes. For example, PlayerPref can store a Player’s personal preferences and be loaded between different VR sections to provide a consistent user experience. In total, we identified 14 Data Tests.

9) **Notification Test:** Notification systems are widely used in traditional and mobile software to deliver messages to recipients. So far, there are no built-in notification APIs provided by Unity for VR applications. Developers customize their own notification system and may present messages in a variety of formats. Notification Tests ensure that the notification system behaves as expected. Based on our observations, no matter what the format of the notifications is, they are tested in PlayMode. For example, when certain conditions are dynamically triggered, developers pause the updates for all other GameObjects by invoking `StopAllCoroutines()` API. Then, they only focus on the animation of the notification message delivery. Eventually, developers resume updates by calling `StartCoroutine()` for the other objects. We found 7 tests of this category.

10) **App Logic Test:** App Logic Test is relevant to a specific VR application based on its business logic. 86 tests from this category were found. To provide a more complete understanding of the App Logic Test category, we divided it into ten different sub-categories. (1) Achievement Property Test: evaluates the correctness of the achievement system (2) Score Property Test: works closely with the achievement system in VR Games to keep track of a player’s progress and give them rewards or penalties based on their performance. (3) Utility Test: a collection of criteria tests that evaluate utility-related methods, which are methods that execute common, often-repeated functions. (4) Map Property Test: verify that vector data files are correctly displaying the map. It can be generalized to evaluate if a VR scene is displayed properly. (5) Exception Test: check if a test method behaves as intended during the execution of the program. (6) Authentication Test: ensure a correct data verification using token error messages and token statuses. (7) Data Structure Test: verify the implementation correctness of customized data structures. (8) GameObject Creation and Deletion Test: evaluate the dynamic creation and deletion of GameObjects within PlayMode. (9) Location Tests: verify the position values (e.g., longitude, latitude) in a 3-D world. Finally, (10) Virtual Fixture Tests: check the correctness of the presentation of a pre-defined navigation path in a virtual environment.

We believe this taxonomy allows VR developers to identify the different areas and aspects of testing they should focus on within their projects. This is especially important due to the apparent lack of established VR testing practices, as well as the several issues noted with testing prevalence, effectiveness, and quality, as found within Sections IV-A to IV-C which is concerning since modern VR headsets and their applications have been around since 2016 [48].

It’s important to note that the Unity platform supports not only the development of VR applications but also that of non-VR applications. Thus, various Unity APIs can serve similar functionalities in both types. Consequently, the taxonomy we defined may also partially apply to test cases in non-VR applications. It is difficult to clarify which APIs are specific to VR by only studying the official documentation. To identify the test categories unique to Unity-based VR projects, we constructed a set of non-VR projects through a process detailed within Section III-A and conducted a second manual analysis on their test cases to determine which test categories they did not cover. The four missing main categories were Audio Test, Physic Test, GUI Test, and Animation Test. The four missing sub-categories were Camera Prop and Rendering Test from Graphic Test, Player Pref Test, and Concurrent Data Access from Data Test.

Based on the previously-detailed definitions, Physics Test, Animation Test, Camera Prop Test, Rendering Test, and Player Pref Test evaluate the correctness of the simulated world’s features. GUI Test, Audio Test, and Concurrent Data Access Test vary depending on a project’s implementation and design. Two of the non-VR projects analyzed are non-graphical libraries, also referred to as Tools, and do not simulate virtual environments. Hence, they contain none of these test categories. The other two are respectively a 2-D card Game and a 3-D puzzle Game. Both present a single view of the entire virtual world and are not designed to dynamically update a user’s viewpoint and regenerate the graphics. Hence, it’s not surprising that they contain neither Camera Prop Tests nor Rendering Tests. Also, no Physics Tests were found because these two projects do not design the physics effects between their objects. In other words, all objects do not move and will not overlap with each other. Although we did not identify any test cases in the GUI Test, Audio Test, and Animation Test in the two non-VR Games, we detected their related APIs in their source code. These findings hint at a lack of testing in current non-VR Game applications similar to their VR counterparts.

V. Threats to Validity

On construct validity, the main threat is the soundness of the automatic analysis results. To measure the design quality of the test cases, we followed the work of De Bleser et al. [28] and selected six test smell types, including Assertion Roulette, General Fixture, Sensitive Equality, Eager Test, Lazy Test, and Mystery Guest. To further validate the automated reports,
we manually labeled smell types of 220 test methods, with a 0.92 kappa score on average, among the two co-authors who worked separately. Automatic test smell detection results show an average of 91.35% accuracy score, a 92.62% recall, and a 91.98% F-1 score. Hence, we believe our automatic analysis results correctly represent the quality of VR test cases.

On internal validity, the threat is potential bias when answering RQ4. Since there is no existing taxonomy to use as a reference, three co-authors reviewed and categorized VR test methods separately. Then, they carried out voting and discussion to finalize the results. In addition, when defining the VR test taxonomy, the paper uses a general language and adds code examples to reduce the gap between the theory and the observed practice.

On external validity, the main concern is the representativeness of studied projects. Our empirical study consisted of 97 open-source Unity VR projects from Nusrat et al. [19]. These projects have been carefully selected with at least 100 commits per-project, and the dataset covers 7 different versions of Unity frameworks (from Unity 4 to Unity 2021). Furthermore, we considered both small-scale projects and large projects backed by companies. This allows us to uncover insight that may reflect general characteristics of all VR applications. Moreover, the taxonomies defined in RQ4 do not depend on Unity alone and can be extended to more general scenarios. In addition, the 4 non-VR projects used within the analysis to detect the VR-specific test categories were selected using the exact same criteria as their VR counterparts, and contain both Tool and Game projects. Thus, we believe our findings provide insight for future test automation design.

VI. RELATED WORKS

A. Study on Software Testing

Software testing is an essential but costly and effort-intensive activity of software development. This has pushed the research community to study software testing practices. Greiler et al. [5] conducted a qualitative study in which they interviewed 25 practitioners about how they test Eclipse plugins. They identified that unit testing plays a critical role, whereas integration problems are identified by the community. Kochhar et al. [6] performed a study on 20,000 non-trivial software projects and explored the correlation of test cases considering various factors. The study discovered that as projects grow in size, their ratio of test cases per LOC decreases. Pecorelli et al. [8] performed an empirical study targeting 1,780 open-source Android apps and identified that the effectiveness of their test cases is low and that they suffer from quality issues. Several other studies [11, 12, 13, 14, 15] also performed empirical analyses of software testing practices and different aspects of testing adoption. Even though these works performed empirical analysis on general-purpose and Android app testing practices, none of the work performed an analysis on testing practices of VR applications.

B. Study on Game Development and VR

As Game and Virtual Reality (VR) applications are becoming more popular and accessible, the research community has started studying the development practices of Game and VR projects. To identify common bugs in Game applications, Truelove et al. [49] performed empirical analysis on 12,122 bug fixes from 723 updates of 30 popular games. Poliowski et al. [50] performed a survey to understand existing testing practices within Game development. Recently Nusrat et al. [19] performed a study on 100 Unity VR applications and created a performance bugs taxonomy in the context of VR. Although there are several works related to VR and Game development, none of them analyzed VR-testing’s adoption, practices, and characteristics by analyzing existing code bases. In this work, we tried to fill this knowledge gap by analyzing existing projects and their testing practices.

VII. IMPLICATIONS

Our analysis pointed out some critical factors and observations for VR application testing which can be beneficial for VR developers, tool builders, and researchers. The findings of this paper lead to the following implications.

For VR Developers: RQ1, RQ2, and RQ3 clearly point out that VR testing’s effort and effectiveness are low and that it suffers from quality issues. These results illustrate the problematic state of testing within VR applications, and that VR developers and testers should put more effort into improving the quantity, coverage, and quality of their tests. In addition, RQ4 generates a VR test case taxonomy based on testing goals, which can be helpful for VR developers as a general guideline that directs the formulation of their test cases.

For VR Tool Builders: RQ2 points out the necessity of tool support for VR application code coverage analysis. Even though Unity provides tool support for code coverage measurement, the tool is unusable in a lot of cases due to compatibility issues. Similarly, based on findings from RQ3, tool developers should develop tool support for automatic detection and repair of test smells for VR applications.

For Software Engineering Researchers: From RQ1 & RQ2, it is evident that VR application testing is not sufficient. Researchers can do further studies on barriers to VR application testing and formulate techniques to overcome them. Moreover, RQ3 clearly identifies some of the test smells in VR test code. These smell categories are derived from traditional software test smells. Since VR applications are different from traditional software, researchers can investigate the existence of VR-specific test smells such as rendering smells, GameObject configuration smells, etc. Finally, through RQ4, we identified some common categories of test cases developed for VR applications. Such categorization can be a basis for future research on pattern-based automatic test case generation for VR applications.

VIII. CONCLUSION

In this paper, we conducted the first quantitative and qualitative study on existing test practices of VR applications. We developed the first tool for test effectiveness analysis and test-smell identification for Unity-based projects. Moreover, we manually explored the characteristics of VR test cases and categorized them. Our automatic analysis shows a low
adoption of testing by VR applications, and that their test practices are less efficient and have a lower design quality. Furthermore, our manual analysis resulted in a VR test taxonomy composed of ten main categories, which reflect the characteristics and specificities of VR applications, along with the identification of VR-specific test categories. We hope that our findings on testing practices in VR applications will allow future researchers to determine VR testing challenges and inspire future research on VR test automation.

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