VRExplorer: A Model-based Approach for Automated Testing of Virtual Reality Scenes

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***Abstract*—With the proliferation of Virtual Reality (VR) markets, VR applications are rapidly expanding in scale and complexity, thereby driving an urgent need for assuring VR software quality. Different from traditional mobile applications and computer software, VR testing faces unique challenges due to diverse interactions with virtual objects, complex 3D virtual environments, and intricate sequences to complete tasks. All of these emerging challenges hinder existing VR testing tools from effectively and systematically testing VR applications. In this paper, we present *VRExplorer*, a novel model-based testing tool to effectively interact with diverse virtual objects and explore complex VR scenes. Particularly, we design the Entity, Action, and Task (EAT) framework for modeling diverse VR interactions in a generic way. Built upon the EAT framework, we then present the *VRExplorer* agent, which can achieve effective scene exploration by incorporating meticulously designed path-finding algorithms into Unity's NavMesh. Moreover, the *VRExplorer* agent can also systematically execute interaction decisions on top of the Probabilistic Finite State Machine (PFSM). Experimental evaluation on nine representative VR projects shows that *VRExplorer* consistently outperforms the state-of-the-art (SOTA) approach *VRGuide* by achieving significantly higher coverage and better efficiency. Specifically, *VRExplorer* yields up to 72.8% and 46.9% improvements over *VRGuide* in terms of executable lines of code (ELOC) coverage and method (function) coverage, respectively. Furthermore, ablation results also verify the essential contributions of each designed module. More importantly, our *VRExplorer* has successfully detected two *functional* bugs and one *non-functional* bug from real-world projects.**

I. Introduction

Virtual reality (VR), working together with other relevant technologies, such as Augmented Reality (AR) and eXtended Reality (XR), aims to provide users with an immersive mixed reality (MR) experience [1]. Current VR applications have proliferated in diverse fields, such as medical treatment, education, audiovisual entertainment, training simulations, manufacturing, and gaming [1–6]. According to Fortune's market report [7], the global VR market is projected to grow from $44.4 billion in 2025 to $244.84 billion in 2032.

With the proliferation of VR markets, VR applications are also rapidly expanding in terms of scale and complexity. How to guarantee the software quality of such complex VR applications becomes an urgent need. As a critical procedure of software development, testing can thoroughly evaluate a software to check whether both requirements and functional needs are fulfilled without defects. To cater for this growing demand in VR applications, extensive efforts have been made in VR testing, while many of them still largely rely on manual testing, which remains highly labor-intensive and inefficient [8, 9]. Most recently, several studies have aimed to test VR applications automatically. As an early attempt, *VRTest* [10] explores VR scenes by controlling the orientation of the camera to interact with virtual objects. *VRGuide* [11] has further improved *VRTest* by optimizing exploration routes to circumvent occluded objects. Besides *VRTest* and *VRGuide*, other researchers also explore using other techniques, such as computer vision (CV) and generative artificial intelligence (GenAI) to achieve scene exploration [12] or understanding [13]. However, these testing tools are still struggling to test VR applications with increased complexity.

The challenges in VR testing stem from the *unique features* of VR applications, sharply different from conventional mobile applications and computer software. First, enabled by diverse peripheral devices (e.g., VR headsets, controllers, joysticks, wands, and haptic gloves), VR systems can support a larger *diversity of interactions* (such as grabbing, pressing, touching, pulling, climbing, and shooting) than conventional mobile systems and PCs. Unfortunately, current VR testing tools cannot properly characterize and represent the diverse interaction behaviors. For example, the state-of-the-art (SOTA) VR testing tool, *VRGuide*, can only test virtual objects with the "*click*" interaction. Second, VR applications contain *complex 3D virtual environments* with interactions with virtual objects, thereby introducing a vast exploration state space. Take *EscapeGameVR*, a popular open-source VR gaming application, as an example, which contains 44 scenes, 8,256 GameObjects, and 1,377 C# script files. Third, VR testing often requires completing a sequence of tasks, e.g., finding a key, then using the key to open a door, next turning a handle, and finally pressing a button to escape. It is non-trivial to accomplish these complex tasks since they involve complex interactions and trigger either events or actions in a specific order. In summary, the diverse and intricate nature of the VR interactions, coupled with large-scale virtual spaces and complex task-completion sequences, makes it difficult to comprehensively and efficiently test VR applications in a systematic and repeatable manner.

Our Approach. To address the above challenges, we present *VRExplorer* to thoroughly test Unity-based VR applications by conducting in-depth scene exploration and comprehensive interactions with virtual objects. Notably, we consider Unity-based VR applications mainly due to Unity's dominant role in VR/MR markets [14]. To tackle the first challenge mentioned above, we design the Entity, Action, and Task (EAT) framework for modeling VR interaction behaviors in a generic way. This hierarchical framework enables a reusable modeling process across VR applications developed by diverse Unity versions and interaction plugins, such as XRIT [15, 16], SteamVR [17–19], and MRTK [20, 21], thereby enhancing

cross-project *generalizability*. To address the second challenge, we present the *VRExplorer* agent built upon the EAT framework. Incorporating meticulously designed path-finding algorithms into Unity's NavMesh, the *VRExplorer* agent can achieve autonomous navigation in 3D virtual environments. Moreover, the *VRExplorer* agent can also systematically execute diverse interaction decisions on top of the Probabilistic Finite State Machine (PFSM). To address the third challenge, the proposed model-based approach transforms intricate VR task execution sequences into structured task models to enable the organized systematic testing and automated execution.

Evaluation. To comprehensively evaluate the proposed *VRExplorer*, we conduct extensive experiments on nine representative VR projects. The experimental results demonstrate that the proposed *VRExplorer* outperforms the SOTA approach *VRGuide* with average performance gains of 72.8% and 46.9% in terms of executable lines of code (ELOC) coverage and method (function) coverage, respectively. Moreover, the ablation study on the five ablated variants of *VRExplorer* also validates the necessity of all modules of the EAT framework. More importantly, *VRExplorer* has successfully detected two previously unknown real-world bugs (i.e., one *functional* bug and one *non-functional* bug), which can nevertheless be detected by the baseline approach. Further, *VRExplorer* has also successfully detected one previously-confirmed bug.

Main Contributions. In summary, we make the following main research contributions:

- We design the EAT framework for modeling complex interaction behaviors and tasks in VR applications. To the best of our knowledge, EAT is *the first* generic three-layer abstraction framework for VR testing based on object-oriented programming (OOP).
- We present *VRExplorer*[1], a novel model-based testing tool to achieve effective interactions with diverse virtual objects and the exploration of complex VR scenes.
- We evaluate *VRExplorer* extensively on nine representative VR projects and demonstrate that it consistently outperforms the SOTA approach in terms of ELOC coverage, method coverage, and interactable object coverage while preserving high efficiency. Moreover, our *VRExplorer* can also successfully detect real-world bugs in VR projects.

II. Background

Interactions in Unity-based VR Applications. A Unity-based VR application typically consists of multiple *Scenes*, each of which is structurally represented by a *hierarchy* of *GameObjects*. These GameObjects represent all visible and interactive elements in the 3D virtual environment and can be composed of various components, such as meshes, scripts, and colliders. Unity provides VR application developers with a rich set of tools for implementing immersive interactions. As Unity's official framework, XRIT [15] can support common VR input modalities such as ray-based selection, direct grabbing, teleportation, and gesture recognition. These interactions are typically implemented using component-based scripts attached to objects, while often relying on trigger colliders or physics events. However, the implementation logic varies significantly across projects, especially when third-party packages are used, thereby increasing the complexity of generalizing automated testing across different VR projects.

Mono Scripts in Unity-based Application Development. In Unity-based VR application development, *Mono* scripts constitute the fundamental building blocks for implementing interactive behaviors. These C# classes inherit properties from Unity's core `MonoBehaviour` [22] base class, enabling them to leverage Unity's component-based architecture. Through the Unity Inspector, developers attach these scripts to GameObjects to create diverse objects. For example, a gun that shoots bullets can be attached with `XRGun`, a class inherited from `MonoBehaviour`, with properties such as a reference to the bullet *prefab*[2], `Shoot()` function, etc.

NavMesh-Based Navigation in Unity. Unity's NavMesh system [23–25] provides a mechanism to traverse 3D environments using navigation meshes generated from static scene geometry. It supports obstacle avoidance, pathfinding, and dynamic updates, making it suitable for simulating players' movement. In VR testing, NavMesh can be leveraged to automate scene exploration by guiding a virtual agent through reachable areas. However, it only supports locomotion and requires external control logic to handle task-specific actions, such as interacting with objects or triggering events.

III. Approach

As shown in Fig. 1, the proposed *VRExplorer* works by first collecting and analyzing open-source VR projects in § III-A. Then, it implements the EAT framework in § III-C after model extraction in § III-B. Next, it conducts testing by *VRExplorer* in § III-D based on the EAT framework, NavMesh, and PFSM.

A. Project Collection and Analysis

To comprehensively investigate the interaction behaviors of VR projects, we collect VR open-source project repositories, which represent diversity in terms of application types, interaction types, and scene types (more details to be given in § V-A) Based on the constructed dataset, we conduct a preliminary analysis and extract the abstraction model consisting of both Object abstraction and Action abstraction, as shown in Fig. 1. After analyzing scenes' hierarchies and core logic code, we can eliminate *non-interactable* objects, which have no relations to the core *interactable* objects (to be tested). These non-interactable objects include static game walls, lighting, the game manager, etc. Further, we deeply dive into the interaction scripts inherited from the `Monobehaviour`, via which these interactable objects are attached in the Unity Inspector. Notably, we also consider the interaction scripts developed by the third-party VR interaction libraries that are attached. This in-depth analysis provides insights into VR interactable objects' key features and facilitates Model Abstraction.

[1]https://anonymous.4open.science/r/VRExplorer-683A/

[2]In Unity, a prefab is a reusable asset template that encapsulates GameObjects and components, enabling efficient instantiation and modular design.

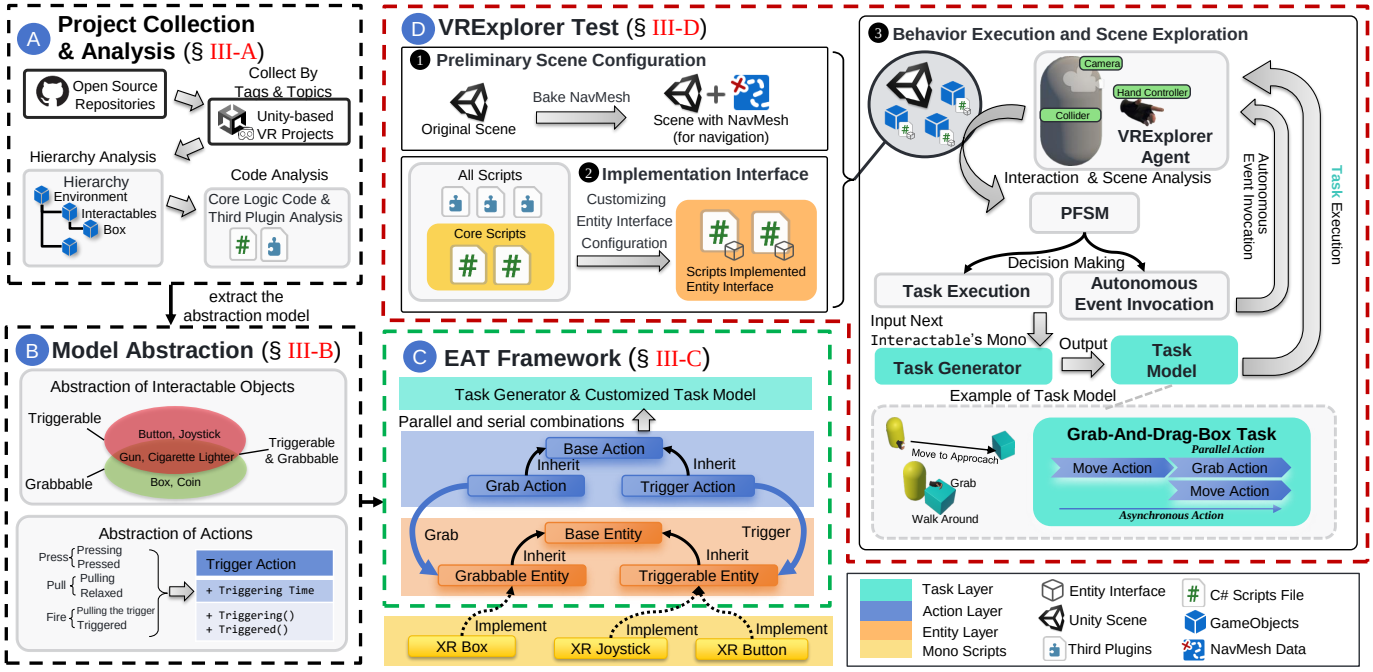


Fig. 1: Overview of *VRExplorer*

B. Model Abstraction

After project analysis, we conduct model abstraction by generalizing VR interactable objects into abstract objects and classifying common VR interaction behaviors into abstract actions based on OOP, as shown in Part B in Fig. 1.

TABLE I: Example of Generalizing VR Interactable Objects

VR Interactable Objects	Interactable Features
Box, Coin, etc.	*Grabbable*
Button	*Triggerable*
Joystick	*Transformable*
Gun, Cigarette Lighter, etc.	*Grabbable* and *Triggerable*

Abstraction of Interactable Objects. We first generalize VR interactable objects into abstract objects containing interactable features. Table I gives an example of VR interactable objects with interactable features, which can determine interaction properties. For instance, objects like boxes and coins can be typically classified as *Grabbable*, meaning that they can be picked up, while objects like buttons and joysticks are considered *Triggerable* with two attributes *triggering* and *triggered*. Notably, some objects may possess multiple interactable features. For instance, a gun or a cigarette lighter possesses both *Grabbable* and *Triggerable* attributes, representing complex interactions to support not only grabbing but also acting on it functionally, such as shooting or turning on a button.

TABLE II: Generalizing Interactions into Abstract Actions

VR Interaction Behaviors	Abstract Actions
Move Around, Jump, Fly, etc.	*Move Action*
Press, Pull, Open/Close, Turn On/Off, Fire(Shoot), etc.	*Trigger Action*
Grab, Throw	*Grab Action*
Place, Move Objects	*Transform Action*

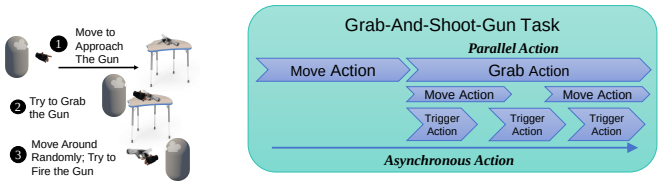
Abstraction of Actions. We then classify VR interaction behaviors into abstract actions. Table II shows an example of a VR interactive scene, in which pressing a button, closing or opening a door, turning on or off a lamp, and pulling a joystick, can be conceptualized as compositions of a continuous process with a following event. Specifically, the player's action – pulling a joystick, can be classified into a continuous pulling process and an event triggered after pulling is over. We classify a behavior with such characteristics into *Trigger Action*.

C. EAT Framework

Based on the model abstraction in § III-B, we propose a three-layer framework called EAT, as shown in Part C in Fig. 1.

Entity Interface Layer. Based on interactable objects' abstraction, we define specific interfaces to encapsulate their corresponding attributes. Particularly, we define a base interface, called `BaseEntity`, which includes the `Transform` property to represent the object's position, rotation, and scale, as well as the `Name` property. Thereafter, all other entity interfaces inherit this base interface. For example, an interface `Triggerable` includes two attributes *triggering* and *triggered* with the `Enum` property. The Entity Interface layer provides customized interfaces tailored to specific features required by the Action layer. Notably, complex interactable features can be efficiently represented through multi-inheritance by multiple interfaces, thereby allowing for higher flexibility and modularity in defining VR interactions.

Action Class Layer. We then extract behaviors with identical characteristics into the same action. We first define an abstract base class, namely `BaseAction` with a *virtual* asynchronous method, `Execute()`. All other action classes inherit this base class. The Action layer can interact with the Entity Interface Layer and provide functional APIs for *VRExplorer* to simulate real players' interactive actions. For example, *Trigger Action* can be concreted into the `TriggerAction` class, which



(a) GASG Process (b) Action Model of GASG task

```
private List<BaseAction> GrabAndShootGunTask(
    IGrabbableEntity grabbableEntity, ITriggerableEntity triggerableEntity)
{
    List<BaseAction> task = new List<BaseAction>()
    {
        new MoveAction(_navMeshAgent, moveSpeed,
            grabbableEntity.transform.position),
        new GrabAction(leftHandController, grabbableEntity,
            new List<BaseAction>()
            {
                new ParallelAction(new List<BaseAction>()
                {
                    new MoveAction(_navMeshAgent, moveSpeed,
                        GetRandomTwitchTarget(transform.position)),
                    new TriggerAction(2.5f, triggerableEntity)
                })
            })
    };
    return task;
}
```

(c) C# Code Snippet of GASG task

Fig. 2: Task Instance of `Grab-And-Shoot-Gun`

consists of an asynchronous method `Triggering()` and a synchronous method `Triggered()`.

Task Model Layer. A composition task consists of multiple *parallel* and *sequential* actions. Parallel action executes asynchronous methods simultaneously, while sequential actions follow a strict order to complete the previous action before proceeding to the next. The Task Model layer includes a task generator and multiple predefined VR interaction tasks. The task generator creates tasks by accepting either a `MonoBehaviour` instance or an array of entities (`BaseEntity[]`). We derive the predefined tasks from commonly used task models. Fig. 2 depicts an example of the `Grab-And-Shoot-Gun` (GASG) task, which consists of three steps: approaching the table, picking up the gun, and shooting while walking in Fig. 2(a). Fig. 2(b) elaborates on the corresponding action model, where the horizontal axis represents the timeline of asynchronous actions starting with *Move Action*, followed by *Parallel Action*, within which three actions execute concurrently. The corresponding code is also shown in Fig. 2(c).

D. VRExplorer Testing

As shown in Part D in Figure 1, *VRExplorer*'s testing process works in three sequential steps: ❶ Preliminary Scene Configuration, ❷ Implementation Interface, and ❸ Scene Exploration with Behavior Execution.

1) Preliminary Scene Configuration: Before scene exploration, we facilitate the agent's navigation capability based on Unity's NavMeshAgent [24] via NavMesh baking. We first configure terrain objects, such as floors and walls, to be static. Regarding those objects that may dynamically move, such as doors, we attach the NavMesh Obstacle [25] component with the enabled Carve option, thereby allowing them to dynamically modify NavMesh. Fig. 3 depicts an example of opening and closing *dynamic* doors.

(a) Doors closed, separating two rooms' NavMesh (b) Doors opened, enabling NavMesh connection

Fig. 3: Dynamic doors with a NavMesh Obstacle component and the Carve option enabled

2) The Entity Interface Layer: On top of the EAT framework, implementing *interactable* interfaces is the core to tackle two challenges: (1) lack of generalizability caused by diverse Unity versions and the fragmentation of the VR development ecosystem; and (2) intricate scene exploration and VR interactions. Using interfaces to encapsulate implementation details can enable testing for a diversity of VR applications.

Procedure 1 Entity Interface Layer Implementation Example.

```
1:  class XRGun implements ITriggerable, IGrabbable:
2:      property TriggeringTime ← 1.5
3:      property Name ← "Gun"
4:      property Grabbable:
5:          if component exists then return it
6:          else add new Grabbable component
7:      method Triggerring() do nothing
8:      method Triggerred() calls Fire()
9:      method OnGrabbed() do nothing
10:     field projectilePrefab: GameObject
11:     field startPoint: Transform
12:     field launchSpeed: float
13:     method Fire():
14:         Instantiate projectile and apply forces
15:     method ApplyForce(rigidbody):
16:         Calculate and apply physics forces
```

To ensure coverage and verify the reliability of interaction methods, test engineers need to select and customize the appropriate Entity layer interfaces for the Mono scripts related to the core VR interaction logic in the target project with the corresponding interface functions implemented. Take Procedure 1 as an example[3], in which a gun class `XRGun` possessing both *Grabbable* and *Triggerable* features, can be implemented by inheriting `MonoBehaviour` while simultaneously implementing the `IGrabbable` and `ITriggerable` interfaces. This design allows the gun object to be both *grabbed* and *triggered* during VR interactions without additional script components. This approach allows `XRGun` to seamlessly integrate multiple interaction capabilities (i.e., *grabbable* and *triggerable*). Leveraging interface composition, we can flexibly define and extend object behaviors without modifying the base class hierarchy, thereby promoting code reusability and achieving modular design in the VR interaction system.

3) Scene Exploration with Behavior Execution: After completing the scene configuration and implementing interactable interfaces, *VRExplorer* automatically performs scene exploration and VR interactions by executing the correspond-

[3]The implementation of the entity interface's code lines is marked blue.

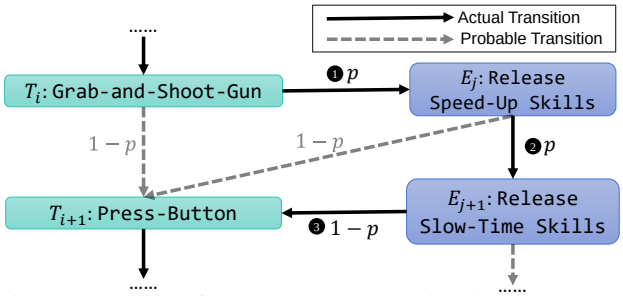


Fig. 4: Example of PFSM State Transition in a VR Scene.

ing behaviors. We design two types of behaviors for *VRExplorer*: *task execution* and *autonomous event invocation*. When executing tasks, *VRExplorer* perceives the scene and inputs `MonoBehaviour` instances or an array of entities (`BaseEntity[]`) into the task generator to obtain and execute the corresponding tasks. Notably, autonomous events reveal that players in VR environments not only interact with objects but also invoke autonomous events, such as casting skills to gain acceleration buffs.

PFSM. To comprehensively cover such testing cases, *VRExplorer* maintains a configurable list of `UnityEvents`, allowing test engineers to easily customize the functions to be covered by configuring them in the Inspector before testing. These two types of behaviors constitute the behavior space, where each behavior can be regarded as a node. The behavior space itself forms a directed graph composed of these nodes. For behavior decision-making, *VRExplorer* employs PFSM to determine transitions between nodes, thereby defining the topology of the directed graph. We use $\mathcal{T} = \{T_1, T_2, \ldots, T_N\}$ to denote the set of all task states, where T_i represents the i-th task state in the execution sequence, with $i \in \{1, 2, \ldots, N\}$. Similarly, we use $\mathcal{E} = \{E_1, E_2, \ldots, E_M\}$ to denote the set of exploration states, where E_j represents the j-th exploration state in the execution sequence, with $j \in \{1, 2, \ldots, M\}$. At each decision point in PFSM, a variable determines the transition direction. The probability of transitioning to an exploration state (E_j) is denoted by p while the probability of transitioning to a task state (T_i) is $(1-p)$. Fig. 4 depicts an example of state transition in a VR scene, where `Speed-Up Skills` node and `Slow-Time Skills` node are two example nodes of an autonomous event adding buffs to the player, while GASG node and Press-Button (PB) node are two example nodes of the task. Those four nodes are independent of each other, while the PFSM is responsible for decision-making and state transitions among them. Table III lists all the state transitions.

TABLE III: State Transition Table of PFSM

Current State	Next State	Condition	Probability
T_i	T_{i+1}	Default	$1-p$
T_i	E_j	Default	p
E_j	E_{j+1}	Default	p
E_j	T_{i+1}	Default	$1-p$
T_i	T_{i+1}	$\mathcal{E}$ exhausted	1.0
E_j	E_{j+1}	$\mathcal{T}$ exhausted	1.0

Path-finding for Navigation. In the path-finding process for navigation, we implement two algorithms: (i) a Greedy algorithm, which follows a local optimization strategy based on the shortest path principle, and (ii) a Backtracking algorithm with Pruning, which searches for globally optimal solutions. Since the Greedy algorithm significantly reduces the time complexity and aligns well with the real-time requirements of VR application testing, we mainly adopt it in our experiments.

In summary, *VRExplorer* continuously obtains scene information, decides the current behavior to execute, and receives feedback after performing the behavior. This process is repeated until all interactable objects and events are covered.

IV. Evaluation of *VRExplorer*

A. Implementation

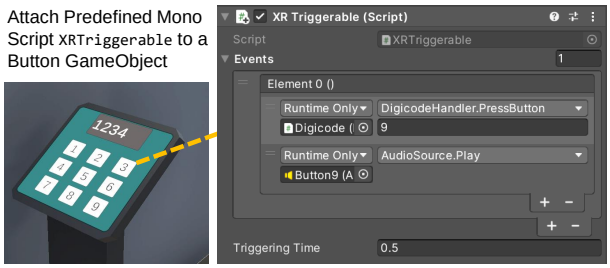


Fig. 5: Predefined Mono Script Component `XRTriggerable`

Implementation of the EAT Framework. We derive `Grabbable`, `Transformable`, and `Triggerable` interfaces from the base interface `BaseEntity` in the Entity layer. In the Action layer, we define `GrabAction`, `MoveAction`, `ParallelAction`, `TransformAction`, and `TriggerAction` as the subclasses of the abstract base class `BaseAction`. Each subclass overrides the `Execute()` method to implement its corresponding behavior. Thereafter, we provide the implementations of common task models as the code-level compositions of actions, e.g., the PB and GASG tasks, as shown previously in Fig. 2(c).

Implementation of the Entity Interface layer. For each project, we analyze the interactable objects in scenes and all the C# scripts referenced by the objects. We select codes that are relevant to the VR interaction logic, they are also called *Core Code*. We then modify scripts (classes) in *Core Code* to implement the interfaces of the Entity Interface layer (measures to diminish this threat to internal validity to be given in § VI). To mitigate the additional workloads caused by implementing such interfaces on developers, we provide a set of predefined scripts inherited from `MonoBehaviour` for the projects developed by the XRIT framework. These commonly used Mono scripts have already been implemented in the corresponding interfaces. Therefore, we can also attach the predefined Mono C# script (as given in § III-D2). Take Fig. 5 as an example, in which test engineers can simply add the predefined Mono scripts that we provide onto the target objects and flexibly configure the functions (methods) under test by adding events to `UnityEvent` [26] in the Unity Inspector. This design can be easily extended to diverse interactions without introducing too many additional workloads to developers.

Implementation of *VRExplorer*. We equip the *VRExplorer*'s GameObject with a NavMeshAgent component for

navigation on NavMesh with the attached controller component (like a player's hands) to enable interactions with objects. To support scene perception, we implement the `EntityManager` class, which is responsible for registering scene information and providing APIs for scene analysis within *VRExplorer*. Then, we implement PFSM to support conditional branching for decision-making, where PFSM's inputs are derived from scene analysis. Next, we implement a `TaskGenerator` component to support task execution by translating relevant inputs into the corresponding task model.

Environment. We implement and evaluate *VRExplorer* with the comparison of other baselines (in § IV-C) on a computer with AMD Ryzen 7 5800H with Radeon Graphics CPU, 32GB RAM, and NVIDIA GeForce RTX 3060 GPU (6GB) Graphics card. This computer is installed with MS Windows 11 and the same Unity version as that used in all evaluated projects.

System Configuration Parameters. Since the proposed *VRExplorer* simulates a player to explore the VR scene, the *initial position*, the *move speed* (MS), and the *turn speed* (TS) (also called *rotation speed* in [11]) greatly affect the testing performance. In particular, we let the center of the scene be the initial position. Regarding the move speed, excessive speed can introduce physical and interactive issues (e.g., test tools may unintentionally move out of a platform due to inertia), although a faster speed may generally improve performance. Therefore, to balance efficiency with practicality, we choose MS = 6 m/s and TS = 60 deg/s as the standard parameters for *VRGuide* and *VRExplorer* in all subsequent experiments. § VI discusses the rationale for these settings. Since these parameters are chosen to be the same for all test tools, they are not repeated in detail in the subsequent experimental results. The experiment is terminated when the test tool reaches convergence. In the PFSM model, the probability of transitioning to the next state is decided by the parameter p, which is set to 0.5, indicating the same propensity for both state transitions.

B. Metrics

With reference to [11, 27–29], we consider executable lines of code (ELOC) coverage, method coverage, interactable objects coverage, and convergence time as evaluation metrics:

- **ELOC Coverage.** Since ELOC mainly focuses on code lines containing executable programs, *ELOC coverage* measures the percentage of these executable lines with the exclusion of blank lines, comments, and declaration statements during testing. We adopt Code Coverage [30], an official tool provided by Unity, to automatically record the ELOC coverage of C# scripts. Running in Unity Editor Mode, the testing tool exports the coverage data as both a historical report in `.html` format and summary data in `.xml` format.
- **Method Coverage.** Besides ELOC coverage, we also consider *method coverage* to evaluate the performance. The method coverage quantifies the percentage of testing methods (functions) that have been invoked during testing.
- **Interactable Object Coverage (IO Coverage).** To fairly compare the proposed *VRExplorer* with SOTA baseline *VRGuide* [11], we also consider IO coverage. However, slightly different from [11], in which interactable objects only include objects that can receive mouse "click" events, we further extend interactable objects to all objects that can be *triggered*, *grabbed*, *moved*, and *transformed*. These interactable objects are identified by analyzing and confirming the `MonoBehaviour` scripts associated with the scene objects.
- **Convergence Time.** Rather than considering the coverage performance, we also evaluate the efficiency of the proposed approach. Particularly, we consider *convergence time* to measure how fast a tool can reach the *converged state*, which is defined as the status at which the testing tool no longer seeks additional scene exploration. The convergence time refers to the amount of time taken for the testing tool to reach the converged state from the initial state.

C. Baselines

Given the unique characteristics of VR applications, such as complex VR interactions and the fragmented nature of the VR development ecosystem, current automated game testing tools and Android application testing frameworks are not suitable for VR application testing. To the best of our knowledge, *VRGuide* [11] is the SOTA automated testing approach for VR applications. Besides *VRGuide*, *VRTest* [10] is a previous version, which nevertheless has inferior performance to *VRGuide* in terms of both method coverage and IO coverage (only pointer click events received).

V. Experimental Results

We conduct extensive experiments to evaluate *VRExplorer* and aim to investigate three research questions (RQs):

- **RQ1:** How does *VRExplorer* perform with comparison of the existing SOTA approach in terms of various performance metrics in diverse VR projects?
- **RQ2:** How do different modules contribute to the performance of *VRExplorer*?
- **RQ3:** Can *VRExplorer* detect real-world VR bugs?

A. VRExplorer Performance

Constructing VR Projects for Evaluation. To evaluate the proposed *VRExplorer*, we construct a project dataset[4], consisting of nine representative VR projects, as summarized in Table IV. This project dataset can be divided into two groups: (1) Group 1, in which we select the most complex three projects also being included in *VRGuide* [11], and (2) Group 2, into which we introduce the other six Unity-based VR projects developed by more recent versions (e.g., after 2020.x). It is worth noting that we construct Group 1 (with relatively older Unity versions) primarily for a fair comparison with *VRGuide*, as it only supports the "click" interaction. Compared with Group 1, Group 2 contains VR projects developed by recent Unity versions, which can support more diverse interactions (while not being supported in *VRGuide*).

The nine projects selected for experiments represent a diverse and comprehensive subset of VR applications. Firstly,

[4]List of constructed project dataset can be found at https://anonymous.4open.science/r/VRExplorer-683A/Artifacts/Evaluated_Repo_Url.md

TABLE IV: Quantitative Metrics of Selected VR Projects

	Projects	# of Scripts	LOC	# of Files	Scenes	# of GOs	Version
Group 1	UnityVR	150	24,858	330	3	124	2019.x
	unity-vr-maze	158	25,261	212	1	278	5.x
	UnityCityView	182	28,335	446	34	1,194	2019.x
Group 2	EscapeGameVR	91	6,659	1,377	44	8,256	2021.x
	VR-Basics	62	2,677	724	5	2,143	2021.x
	VGuns	81	10,900	848	36	1,653	2020.x
	EE-Room*	88	4,450	1,063	8	1,517	2020.x
	VR-Room	65	3,660	679	2	414	2022.x
	VR-Adventure	11	260	91	2	288	2022.x

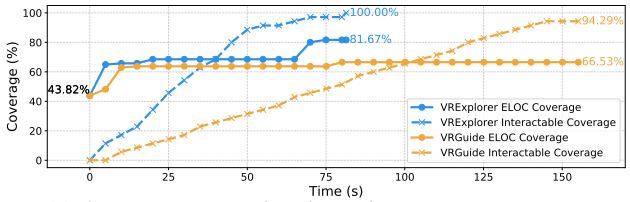
* EE-Room stands for Edutainment-Escape-Room.

the chosen projects cover all of the most commonly featured VR application types as defined in [31]: (i) Action and Shooter (`VGuns`), (ii) Simulation (`VR-Basisc`, `VR-Room`, `UnityVR`), (iii) Adventure (`unity-vr-maze`, `VR-Adventure`), and (iv) Puzzle (`Edutainment-Escape-Room`, `EscapeGameVR`). This diversity ensures that the experimental results are generalizable across different VR genres and interaction manners. Second, these projects cover a wide range of Unity versions, from older releases like 2019.4.2f1 (`UnityCityView`) to more recent versions such as 2022.3.7f1 (`VR-Adventure`), as well as the legacy version 5.4.1f1 (developed for `unity-vr-maze`). This version diversity ensures that our testing approach is evaluated across different Unity engine environments, demonstrating its robustness and compatibility. Moreover, the selected projects exhibit a variety of scales and complexities. For instance, the number of C# scripts ranges from as few as 11 in `VR-Adventure` to over 90 in `EscapeGameVR`, with LOC spanning from around 260 to over 6,600. This selection allows us to assess the testing tools' versatility from small and medium-sized VR applications to large ones. These projects also differ in the number of scenes and the number of GameObjects (GOs), with some projects like `EscapeGameVR` having 44 scenes, reflecting complex and rich environments, while others like `VR-Room` have fewer scenes but have potentially dense and complicated interactions.

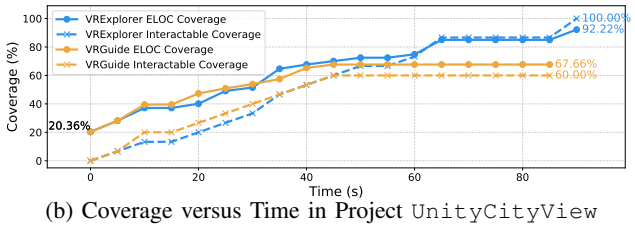
Results on Projects of Group 1. Fig. 6 shows the trend of ELOC coverage versus time when testing all the projects in Group 1. Table V shows the experimental results of *VRExplorer* with the comparison of the baseline approach *VRGuide* on the three projects in Group 1. To quantitatively evaluate the performance improvement of *VRExplorer* over *VRGuide* (or other compared methods in § V-B), we define the *performance gain* of method A over method B as follows,

$$G_{AB} = \frac{P_A - P_B}{P_B} \times 100\%, \tag{1}$$

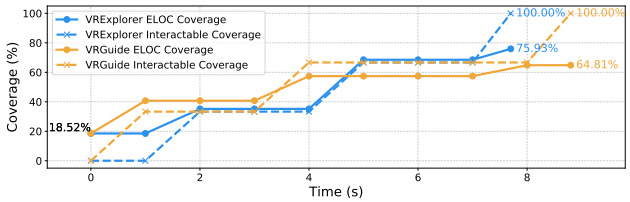
where P_A and P_B denote the performance metrics achieved by methods A and B, respectively. For example, we evaluate the ELOC performance gain of *VRExplorer* over *VRGuide* in project `unity-vr-maze` by $G_{EG} = \frac{P_E - P_G}{P_G} \times 100\% = \frac{81.67-66.53}{66.53} \times 100\% = 22.8\%$. Similarly, we have the performance gain of *VRExplorer* (E) over *VRGuide* (G) in terms of method coverage and IO coverage by 16.7% and 6.1%, respectively. Meanwhile, our *VRExplorer* reduces the convergence time cost by 43.9% compared with *VRGuide*. For project `UnityCityView`, *VRExplorer* achieves performance gains in terms of ELOC coverage, method coverage, and IO coverage over *VRGuide* by 36.3%, 27.6%, and 66.7%, respectively. Our



(a) Coverage versus Time in Project `unity-vr-maze`



(b) Coverage versus Time in Project `UnityCityView`



(c) Coverage versus Time in Project `UnityVR`

Fig. 6: ELOC Coverage* versus Time during the Testing Process of projects in Group 1.

*Initial ELOC Coverage is identical across projects as initialization code (e.g., `Awake()`) runs immediately, regardless of interactions.

VRExplorer achieves consistent performance gains in project `UnityVR`, e.g., ELOC coverage gains by 17.1% and method coverage gain by 9.1%, with the reduced convergence time by 12.5%. Notably, our *VRExplorer* achieves 100% IO coverage in all three projects while *VRGuide* can only achieve 100% IO coverage in project `UnityVR`. In summary, experimental results demonstrate that the proposed *VRExplorer* consistently outperforms *VRGuide* in coverage performance and efficiency.

Results on Projects of Group 2. Table VI shows the experimental results of *VRExplorer* with the comparison with the baseline approach *VRGuide* on the six representative projects in Group 2 in terms of ELOC coverage and method coverage. Notably, we omit the IO coverage here mainly because *VRGuide* exhibited lower IO coverage than our *VRExplorer* due to its sole "clicking" interaction. Therefore, we primarily focus on the code coverage (ELOC and method coverage) of the core development logic of VR projects.

We observe that our *VRExplorer* consistently outperforms *VRGuide* in all six projects. In particular, for project `VR-Basics`, *VRExplorer* achieves ELOC coverage and method coverage gains over *VRGuide* by 93.8% and 72.8%, respectively. For project `VR-Room`, *VRExplorer* achieves ELOC coverage and method coverage gains by 89.4% and 65.0%, respectively. It is worth noting that *VRExplorer* achieves ELOC coverage and method coverage gains by 170.7% and 100.0%, respectively, in project `VGuns`, showcasing its strength in handling more complex and diverse VR testing scenarios.

Comprehensively considering experimental results in all the nine projects in both Group 1 and Group 2, *VRExplorer* has achieved average ELOC coverage gain by 72.8% and average

TABLE V: Results on Projects in Group 1

Projects	Approaches	ELOC Coverage (%)	Method Coverage (%)	IO Coverage(%)	Convergence Time Cost (s)	# of Interactable Objects
unity-vr-maze	VRGuide	66.53	70.59	94.29	145.0	35
	VRExplorer	81.67 (+22.8%)	82.35 (+16.7%)	100.00 (+6.1%)	81.4 (-43.9%)	
UnityCityView	VRGuide	67.66	78.38	60.00	45.0	15
	VRExplorer	92.22 (+36.3%)	100.00 (+27.6%)	100.00 (+66.7%)	89.3 (+98.4%)	
UnityVR	VRGuide	64.81	84.62	100.00	8.8	3
	VRExplorer	75.93 (+17.1%)	92.31 (+9.1%)	100.00	7.7 (-12.5%)	

TABLE VI: Results on Projects of Group 2

Projects	Approaches	ELOC Coverage (%)	Method Coverage (%)
VR-Basics	VRGuide	41.38	53.22
	VRExplorer	80.17 (+93.8%)	91.93 (+72.8%)
VR-Room	VRGuide	40.97	50.63
	VRExplorer	77.61 (+89.4%)	83.54 (+65.0%)
VGuns	VRGuide	28.68	38.89
	VRExplorer	77.57 (+170.7%)	77.78 (+100.0%)
VR-Adventure	VRGuide	54.12	65.00
	VRExplorer	91.76 (+69.6%)	95.00 (+46.2%)
EE-Room	VRGuide	38.08	58.06
	VRExplorer	70.61 (+85.5%)	88.17 (+51.8%)
EscapeGameVR	VRGuide	41.77	55.26
	VRExplorer	71.08 (+70.2%)	73.68 (+33.3%)

TABLE VII: Results of Ablation Study

Projects	Approaches	ELOC Coverage (%)	Method Coverage (%)
VR-Basics	VRGuide	41.38	53.22
	VRExplorer	<u>80.17</u>	<u>91.93</u>
	VRExplorer w/o *T*	68.10 (-15.0%)	77.42 (-15.9%)
	VRExplorer w/o *Tf*	59.24 (-26.1%)	70.00 (-16.2%)
VR-Room	VRGuide	40.97	50.63
	VRExplorer	<u>77.61</u>	<u>83.54</u>
	VRExplorer w/o *G*	58.52 (-24.6%)	69.62 (-16.4%)
	VRExplorer w/o *T*	64.12 (-17.3%)	67.00 (-19.7%)
VGuns	VRGuide	28.68	38.89
	VRExplorer	<u>77.57</u>	<u>77.78</u>
	VRExplorer w/o *TG*	50.37 (-35.3%)	61.11 (-16.7%)
	VRExplorer w/o *AE*	65.07 (-16.1%)	63.89 (-17.9%)

method coverage gain by 46.9% compared to *VRGuide*. Experimental results demonstrate that *VRExplorer* outperforms *VRGuide* (in diverse performance metrics) consistently across various VR projects, which were developed with different versions of the Unity engine.

Answer to RQ1: Experimental results on all nine representative VR projects demonstrate that *VRExplorer* outperforms the SOTA approach *VRGuide* in terms of ELOC coverage, method coverage, and IO coverage. In particular, *VRExplorer* achieves the average performance gains over *VRGuide* in terms of ELOC coverage and method coverage by 72.8% and 46.9%, respectively, across all the projects. Moreover, *VRExplorer* converges faster or comparably faster than *VRGuide* while maintaining substantially higher coverage. These performance improvements are observed across diverse real-world VR scenarios, demonstrating the proposed *VRExplorer*'s strong generalizability in covering code and interactable VR objects during automated testing.

B. Ablation Study

To investigate the contribution of each module in the EAT framework of the proposed *VRExplorer*, we conduct a comprehensive ablation study by selectively removing one interaction module from *VRExplorer*. We then evaluate these methods by comparing them with the full-fledged *VRExplorer* framework in terms of ELOC coverage and method coverage. Notably, we also compare them with *VRGuide* to investigate the performance improvement contributed by each module.

Ablation Experiment Configuration. As described in § III-C, interaction behaviors play a crucial role in the EAT framework. To investigate these interaction behaviors, we remove a specific interaction from a tested project's modules (provided that this module is used in this project). For example, we obtain *VRExplorer* w/o *T* by removing the *Triggerable* module from the Entity layer's interface `Triggerable`, the Action layer's class `TriggerAction`, all tasks involve triggering in the Task layer, and the corresponding Mono C# scripts `XRTriggerable.cs`. Similarly, we obtain *VRExplorer*'s other ablated variants: VRExplorer w/o *Tf* (without *Transformable*), VRExplorer w/o *G* (without *Grabbable*), VRExplorer w/o *TG* (without both *Triggerable* and *Grabbable*)), and VRExplorer w/o *AE* (without *autonomous event*).

Results of Ablation Study. Table VII presents the experimental results of the ablation study in terms of the ELOC coverage and method coverage in three projects: `VR-Basics`, `VR-Room`, and `VGuns`, where the best result is highlighted with an underline. These ablation experiments cover all the *VRExplorer*'s variants and span all the Unity versions of the projects in Group 2 (from 2020 to 2022). Specifically, we compare *VRGuide* and *VRExplorer* with its five ablated variants: *VRExplorer* w/o *G*, *VRExplorer* w/o *T*, *VRExplorer* w/o *Tf*, VRExplorer w/o *TG*, and VRExplorer w/o *AE*. To quantitatively evaluate the effect of removing each module, we also calculate the performance gain of a method over another compared method according to Eq. (1).

In project `VR-Basics`, the full-fledged *VRExplorer* achieves the best performance in terms of 80.17% ELOC coverage and 91.93% method coverage. We observe that removing the *Triggerable* module causes a 15.0% ($\frac{68.10-80.17}{80.17} \times 100\%$) decrease in ELOC coverage and a 15.9% decrease in method coverage and the removal of the *Transformable* module leads to a 26.1% decrease in ELOC coverage and 16.2% in method coverage. In project `VR-Room`, we also find that the removal of the *Grabbable* module has the most pronounced effect, i.e., reducing ELOC coverage by 24.6% and method coverage by 16.4%. Disabling the *Triggerable* module also leads to an ELOC decrease of 17.3% and a method coverage decrease of 19.7%. In project `VGuns`, we observe that the removal of both the *Triggerable* and *Grabbable* modules causes a 35.3% decrease in ELOC coverage and a 16.7% decrease in method coverage. Moreover, we find that the removal of the *autonomous event* module causes a 16.1% decrease in

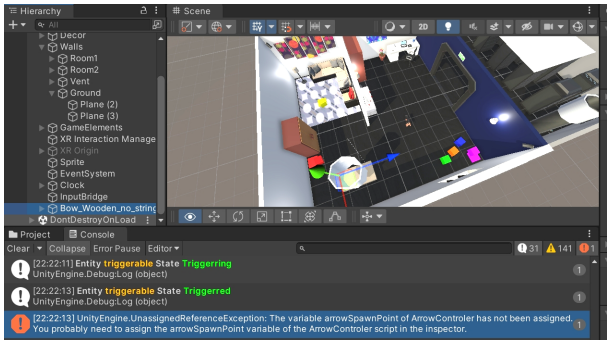


Fig. 7: A Detected Bug in `EscapeGameVR`

ELOC coverage and a 17.9% decrease in method coverage, indicating that the *autonomous event* module we described in § III-D3 also contributes significantly. These results confirm the significant contribution of each interaction module to *VRExplorer* despite various portions across different projects.

Overall, removing any individual module leads to a substantial drop in code coverage (in terms of ELOC coverage and method coverage), further confirming the importance of integrating all three interaction-aware modules in the EAT framework. The full-fledged *VRExplorer* consistently yields the highest code coverage.

Answer to RQ2: Removing any module from the EAT framework leads to a substantial decrease in ELOC coverage and method coverage. The degree of impact caused by the ablated module varies by diverse projects and interaction types. These results validate the necessity and effectiveness of integrating all the modules in the *VRExplorer* for comprehensive interaction-aware VR testing.

C. Bug Detection in VR Projects

Since the primary goal of software testing is to detect or identify potential bugs, we also investigate whether the proposed *VRExplorer* can detect real-world bugs in VR projects. We have scanned all nine projects through comprehensive testing conducted by *VRExplorer*. Thereafter, we have successfully detected two *functional* bugs and one *non-functional* bug in total, from projects `EscapeGameVR`, `UnityCityView`, and `EscapeGameVR`. Herein, a functional bug refers to a bug that causes the VR application not to work as expected, while a non-functional bug denotes a bug not directly related to the functionality (may be relevant to performance and usability issues). Notably, two functional bugs have been found in projects `EscapeGameVR` and `UnityCityView` while we have detected one non-functional bug in project `EscapeGameVR`. Moreover, the bug from `UnityCityView` has been fixed by developers (after checking the commits), while two bugs from `EscapeGameVR` reported by us have not been confirmed by developers so far. Our *VRExplorer* can detect all these VR bugs, which are either functional or non-functional. Although *VRGuide* is able to detect the bug in project `UnityCityView`, it misses the other two bugs in project `EscapeGameVR`.

Fig. 7 shows a screenshot of one functional bug detected by our *VRExplorer* in project `EscapeGameVR`. This bug occurs due to *assignment exception*, which can be explained as follows. When a bow releases an arrow, the method `ReleaseArrow()` is invoked with the attempt to access the `arrowSpawnPoint` field of the `ArrowController` class. However, the developers have mistakenly failed to assign a value to this field (or the assignment was unintentionally lost), thereby resulting in an *Unassigned Reference Exception* [32, 33] bug, which is a Unity-specific runtime exception occurring when a serialized reference field (typically declared as `public` or marked with `[SerializeField]` [34]) in a `MonoBehaviour` class is accessed without being assigned a value in the Unity Inspector.

Another non-functional bug in `EscapeGameVR` is caused by the loss of the `ArrowPrefab` resource. This bug can be identified by our *VRExplorer* through a simple manual inspection. The reason why these two bugs are not detected by *VRGuide* is that triggering these two bugs requires complicated actions and multiple types of interactions, while *VRGuide* cannot handle them. Differently, our *VRExplorer* can complete this difficult testing task through our model-based framework. In particular, *VRExplorer* requires the correct placement of three cubes onto platforms of the corresponding color, thereby ensuring that none of them fall outside the designated platform areas. Once this condition is satisfied, a new bow is instantiated. Consequently, triggering the bug needs the bow to be drawn and released by *VRExplorer*. This type of complex interactive task contains two or even more interactive patterns (e.g., *Transformable*, *Grabbable*, and *Triggerable*), which can not be completed by *VRGuide* (only supporting "clicking" interaction), while our approach handles this task properly.

Answer to RQ3: Through testing VR projects, the proposed *VRExplorer* can successfully detect three real-world bugs in VR projects. More importantly, our *VRExplorer* is capable of detecting complex VR bugs, which can only be triggered after complex interactions.

VI. Discussion

Threats to External Validity. Although we have covered as many types of VR applications (developed by diverse Unity versions) as possible, there are still types of scenarios and interaction patterns not fully covered in our approach. Moreover, while our framework is currently tailored for VR applications developed in Unity, it can be extended to support other engines, such as Unreal Engine [35], with further adaptation, thereby enabling its broader applicability.

Threats to Internal Validity. The primary threats to internal validity arise from potential human errors during the selection of *Core Code* and the implementation of the interface. Specifically, during the *Core Code* selection phase, errors could be introduced due to subjective judgment. To minimize this threat, we have leveraged a majority-voting mechanism, where four test engineers (with VR developing experience) have independently selected code segments. The final decision has been made according to the majority vote, thereby ensuring a more objective outcome. Moreover, during the interface implementation phase, potential inconsistencies or biases among test engineers are also present. To address

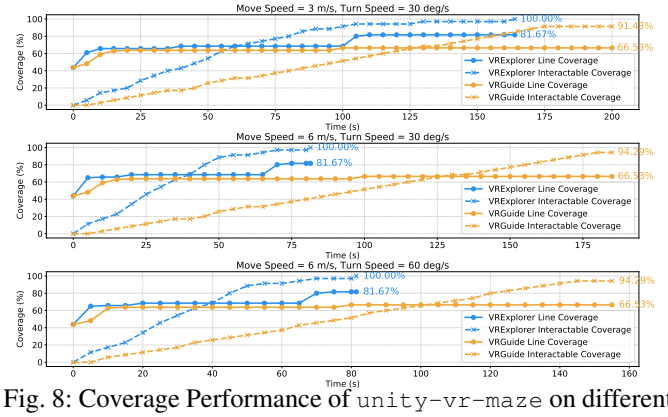


Fig. 8: Coverage Performance of `unity-vr-maze` on different speed parameters (MS and TS)

this threat, we have arranged the four test engineers to collaboratively discuss the design to reach a consensus, thereby helping mitigate discrepancies and ensuring a consistent yet customized implementation.

Impacts of Speed Parameters. To explore optimal speed parameters, we test three sets of values on the `unity-vr-maze` project. Specifically, we have chosen (i) MS = 3 m/s, TS = 30 deg/s, (ii) MS = 6 m/s, TS = 30 deg/s; and (iii) MS = 6 m/s, TS = 60 deg/s. During the experiments, all of the *initial position* metric is fixed at `(0,4.5,0)` to ensure the test tool be legally standing on the floor. Fig. 8 shows the coverage performance of *VRExplorer* with comparison of *VRGuide* in `unity-vr-maze` with different speed parameters. We observe the same trends for all three parameters. In particular, *VRExplorer* takes less time to reach convergence than the baseline approach *VRGuide* with the higher ELOC coverage and IO coverage. These results also indicate that the TS has the minimal impact on efficiency, whereas the MS shows a more significant effect.

Limitations and Future Work. *VRExplorer* still needs to analyze scenes manually and implement customized interfaces, thereby inevitably introducing some extra workloads (despite low) and a certain learning curve for test engineers. As future work, we will improve *VRExplorer*'s analysis capability of automatically understanding VR scenes inspired by recent advances in multi-modal large models. Further, we will also aim to automate the interface implementation and task model generation with the advent of large language models.

VII. Related Work

Automated Game Testing. As a code-based data augmentation technique, GLIB [36] can automatically detect game GUI glitches. Macklon et al. [37] present an approach to automatically detect visual bugs in `<canvas>` games. Prasetya et al. [38] leverage graph-based path-finding techniques to tackle challenges in automated game navigation and exploration. As a Java-based multi-agent programming framework, IX4XR [39, 40] facilitates game testing by enabling test agents to interact with the game under test. As a Belief-Desire-Intention library, APLIB [29] supports the development of intelligent agents capable of executing complex testing tasks. Ferdous et al. [41] propose a model-based approach by leveraging EFSM to model game behavior. However, these game testing approaches are generally tailored to specific types of games instead of VR applications.

Automated Mobile Application Testing. *Stoat* [42] is a stochastic model-based testing tool for Android apps with combined dynamic and static analysis to generate tests. Chen et al. [43] propose a model-based GUI testing approach for HarmonyOS applications with the adoption of the *arkxtest*[44] framework. AutoConsis [45] leverages a specially tailored Contrastive Language-Image Pre-training (CLIP) multi-modal model to automatically analyze Android 2D GUI pages. FASTBOT2 [46] leverages a probabilistic model that memorizes key information for testing based on a model-guided testing strategy. KEA [47] is a property-based testing tool for finding functional bugs in Android apps. However, these mobile application testing approaches can only address 2D GUI testing.

RL-Based Testing. Tufano et al. [48] employ RL to train an agent to play games in a human-like manner to identify areas that lead to FPS drops. RLBT [28] applies a curiosity-based RL approach to automate game testing by maximizing coverage. Bergdahl et al. [49] adopts a modular approach, in which RL complements classical test scripting rather than replacing it. *Wuji* [50] leverages evolutionary algorithms, RL, and multi-objective optimization for game testing. However, RL-based approaches alone are very limited in complex VR scene exploration.

VR Application Testing. Rzig et al. [8] analyze 314 open-source VR applications, revealing that 79% of them lack automated tests. Harms [51] proposes an automated approach that extracts task trees from real VR usage recordings to detect usability smells without predefined tasks or settings. PREDART [9] predicts human ratings of virtual object placements, serving as test oracles in AR testing. *VRTest* [10] extracts information from a VR scene and controls the user's camera to explore the scene and interact with virtual objects. *VRGuide* [11] applies a computational geometry technique called Cut Extension to optimize camera routes for covering all interactable objects. Qin and Weaver [12] explore Generative AI for field of view analysis in VR testing. However, these approaches can not address complicated VR interactions and are not generic for different development ecosystems.

VIII. Conclusion

In this paper, we design the EAT framework, a generic three-layer abstraction framework based on OOP for modeling complex interaction behaviors and tasks in testing VR applications. Based on EAT, we present *VRExplorer*, a novel model-based testing tool to achieve effective interactions with diverse virtual objects and explorations of complex VR scenes. To validate the performance of our approach, we evaluate *VRExplorer* on nine representative VR projects. The experimental results validate our approach's superior performance to the SOTA method in terms of coverage and efficiency, as well as the ability to detect complicated real-world bugs.

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