Hijacking JARVIS: Benchmarking Mobile GUI Agents against Unprivileged Third Parties

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Abstract

Mobile GUI agents are designed to autonomously execute diverse device-control tasks by interpreting and interacting with mobile screens. Despite notable advancements, their resilience in real-world scenarios-where screen content may be partially manipulated by untrustworthy third parties-remains largely unexplored. Owing to their black-box and autonomous nature, these agents are vulnerable to manipulations that could compromise user devices. In this work, we present the first systematic investigation into the vulnerabilities of mobile GUI agents. We introduce a scalable attack simulation framework AgentHazard, which enables flexible and targeted modifications of screen content within existing applications. Leveraging this framework, we develop a comprehensive benchmark suite comprising both a dynamic task execution environment and a static dataset of vision-language-action tuples, totaling over 3,000 attack scenarios. The dynamic environment encompasses 58 reproducible tasks in an emulator with various types of hazardous UI content, while the static dataset is constructed from 210 screenshots collected from 14 popular commercial apps. Importantly, our content modifications are designed to be feasible for unprivileged third parties. We evaluate 7 widely-used mobile GUI agents and 5 common backbone models using our benchmark. Our findings reveal that all examined agents are significantly influenced by misleading third-party content (with an average misleading rate of 28.8% in human-crafted attack scenarios) and that their vulnerabilities are closely linked to the employed perception modalities and backbone LLMs. Furthermore, we assess training-based mitigation strategies, highlighting both the challenges and

opportunities for enhancing the robustness of mobile GUI agents.

1 Introduction

In recent years, GUI agents powered by large language models (LLMs) and vision language models (VLMs) [5, 8, 17– 19, 23–25, 36] have demonstrated remarkable capabilities in task automation, positioning them as promising candidates for next-generation personal assistants. A typical GUI agent takes a user-provided task description (*e.g.* booking a ticket, sending a message, etc.) as input and autonomously interacts with the device (*e.g.* via smartphone touchscreen) to complete the task. The major steps of an agent session include multiple rounds of perception (reading the screen content), reasoning (deciding how to proceed the task on the current screen) and action (performing the decided operation).

However, existing agents are mostly developed and tested in simple and clean environments (*e.g.* emulators and apps without user accounts and dynamic Internet content). When deployed in real-world scenarios, these agents must interact with content from untrustworthy third-party sources that could be deliberately crafted to deceive them. For example, as depicted in Figure 1, consider a mobile agent tasked with reading and summarizing community posts in a social media app, attackers could manipulate the post content and inject hazardous information. When the agent reads the post, it could be misled and perform unexpected actions including posting uncontrolled comments on social media, navigating to unsafe external websites, downloading potentially harmful applications, etc. Similarly, when an agent is tasked with shopping in an e-commerce platform, unfaithful sellers could Conference acronym 'XX, June 03-05, 2018, Woodstock, NY



Figure 1: Example of agent being misled by third-party information in real-world scenarios.

manipulate their product descriptions to influence the decision process of the agent, which could lead to potential financial loss for the user. These real-world threats highlight the critical need to systematically evaluate and improve the robustness of LLM-powered mobile agents against adversarial content.

Existing studies has demonstrated that GUI agents can be easily distracted by either pop-up windows, irrelevant information, or hiding HTML elements [11, 14, 31, 34]. However, these datasets are insufficient to help understand the robustness of mobile agents in realistic scenarios, since their assumed attacks are limited in terms of stealthiness, complexity, and feasibility. First, stealthiness means how difficult the threats can be detected. Existing attacks are mostly based on simple pop-up windows [34] that can be easily identified by human and automated tools, while real-world threats may be much harder to notice, such as a title and description of a product, or the content of a post in social media. Second, the *complexity* of existing threats are mostly low, due to the relatively simple and fixed attack patterns. Attackers can usually design tailored targeted attacks that can lead to agent misbehavior more easily. Finally, feasibility represents whether and how possible the attacks can be actually implemented in real applications. Existing works mostly focus on web-based agents [26, 31, 34], while generating pop-up windows or inserting invisible elements usually require high system permissions, which is infeasible for most third-party attackers on Android devices.

In order to better understand the robustness of mobile GUI agents powered by LLMs, we perform an in-depth empirical study to reveal the impact of real-world misleading contents on seven state-of-the-art mobile agents. We first develop a highly configurable and scalable framework, AgentHazard, to automatically render custom contents on Android applications, making it flexible to simulate vast amounts of real-world attack scenarios with minimal human effort.

The framework mainly consists of a GUI hijacking tool which serves as a native Android application, and an attack module which intercepts system UI state transitions between the agent and the environment. After loading structured attack configurations, the tool monitors system UI state transitions by Android Accessibility events, and modifies UI state information by injecting adversarial content into both the UI element tree and the screenshot in real-time. When agent requests for UI state, the module will return the modified information as it was the real UI state, and record the actions performed by the agent for later analysis. Compared to existing work, our attacks are applied to native components with no obvious visual distinction from the normal interface. Moreover, the attacked regions are areas that third parties have legitimate permissions to modify. This largely addresses the challenges of stealthiness and feasibility. It is proven that our framework is more stealthy and harder to detect compared to existing popup-based approaches, and simple adversarial training cannot provide effective defense.

Based on our framework, we construct a fine-grained benchmark suite that includes a dynamic task execution environment and a static dataset of vision-language-action tuples. Through dynamic injection of misleading content into apps, our benchmark suite simulates how third parties could mislead agents by modifying specific UI element content in real-world scenarios. We design attack scenarios with different levels of complexity, ranging from simple "Click here!" to complex human-crafted adversarial contents. Our dynamic environment includes 58 reproducible tasks, and the static dataset contains 840 vision-language-action tuples. Based on these tasks, we generate over 3,000 attack scenarios with various settings.

Our experiments have shown that, existing mobile agents are vulnerable against a wide range of real-world misleading contents. On the dynamic task execution environment, the misleading contents can lead to significant performance degradation, with up to 36.2% success rate drop, as well as up to 73.3% misleading rate. We also find that the performance of mobile agents is sensitive to the complexity of misleading contents. Through a pattern combining a misleading action and a task target, we observe an average attack misleading rate of 24.8%, up to 45.0%. We also discuss the differences between different modalities of mobile agents, different backend LLMs, and different misleading targets. It is proven that, although incorporating visual modality can improve the performance of mobile agents, it also makes them more vulnerable to misleading contents. Through comparison among a set of backbone LLMs, we find that Claude-3.7-sonnet demonstrates the best performance, achieving the

highest post-attack accuracy score and the lowest misleading rate, followed by DeepSeek-series and GPT-series.

Based on these findings, we finally propose suggestions for improving the robustness and security of LLM-powered mobile agents for future research. We suggest that agents should be equipped with discriminative and cognitive capabilities for information sources, enabling them to consciously distinguish between information from sources with different levels of credibility. On the other hand, we recommend that agents should prompt users when encountering high-severity issues or when high-privilege operations are required, to avoid unnecessary problems.

Our contributions can be summarized as follows:

- We design and implement a highly configurable and scalable **mobile adversarial attack simulation frame-work**, which could inject specified contents as native GUI elements on Android applications without hack-ing or manual modification.
- We construct a **fine-grained benchmark suite** that includes a dynamic task execution environment and a static dataset of vision-language-action tuples, consisting of more than 3,000 attack scenarios.
- We obtain several **valuable insights** about the robustness of mobile agents against adversarial attacks through misleading contents, and provide **guidelines** for future agent design.

The benchmark will be open-sourced to the community.

2 Background and Related Work

2.1 GUI Agents

Large language models (LLMs) [15] and multimodal models (VLMs) [33] have demonstrated increasingly sophisticated capabilities in human-like reasoning. Based on these models, researchers have developed various autonomous agents [29] that interact with different environments to complete tasks through information analysis and decision making.

Among these, GUI agents [16] have emerged as a significant category, capable of understanding graphical user interfaces and executing a series of operations that simulate user actions (*e.g.* clicking and typing). These agents [6, 8, 10, 17, 24, 25, 32] are widely deployed in both Web and mobile applications, establishing their understanding of interfaces through multiple modalities, including visual information from interface screenshots and textual data such as HTML code for web pages or XML interface information for Android mobile devices. Leveraging the understanding and reasoning capabilities of models, GUI agents operate based on their perception of the interface and the current task state, calling upon potential tools or external knowledge bases to plan tasks, ultimately executing actions and updating their state, entering the next round of the "perception-planningacting" cycle. To enhance the performance of GUI agents, numerous studies have been conducted within this framework, such as employing more efficient interface description schemes [10, 24], utilizing knowledge bases and memory modules [25, 38], or training grounding models [6, 8, 12, 28] to achieve more efficient and precise action execution.

2.2 GUI Agent Benchmarks

To effectively evaluate the capabilities of autonomous agents in task execution, researchers have developed numerous benchmarks that fall into two main categories: static and dynamic.

Static benchmarks [4, 5, 9, 13, 19, 22, 30] provide predefined input data such as GUI screenshots and textual interface information (HTML, DOM trees), focusing on specific evaluation metrics like interface comprehension and element localization accuracy, typically assessed through exact matching criteria with predefined ground truth. These static benchmarks enable efficient and convenient evaluation processes, though they lack flexibility in assessing real-world interactions. In contrast, dynamic benchmarks offer interactive environments such as websites [7, 21, 38] or Android emulators [18, 24] where agents can operate with greater freedom within defined parameters. While evaluation in these environments tends to be slower due to their interactive nature, these dynamic frameworks better assess agents' holistic capabilities by allowing them to navigate and complete complex tasks in realistic environments, providing a more comprehensive evaluation of their performance across various scenarios.

2.3 Security and Robustness of GUI Agents

As the capabilities of autonomous GUI agents continue to advance, the issue of security and robustness has become increasingly prominent as well. Drived by language models, agents are exposed to the risk of being attacked by prompt injection [2], jailbreaking [20] and backdoor attacks [35], or other adversarial attacks [1, 3]. Prior work has explored the security vulnerabilities of GUI agents, showing that they can be easily misled by adversarial elements (*e.g.* pop-ups, environmental distractions, malicious tool usage instructions) [11, 14, 27, 34].

Most existing work focuses on web-based attacks, implementing attacks against agents by modifying HTML [31] or adding pop-ups [34], while lacking research on mobile agents. Unlike web environments, mobile operating systems like Android have higher security requirements and stricter control over user privacy, application permissions, and thirdparty content access. To achieve attacks similar to web-based pop-ups or invisible interface elements, typically only app developers have the necessary permissions. Such apps would not only struggle to pass security reviews but would also rarely be encountered during normal agent usage, making it impractical to directly transfer existing web-based attack approaches to mobile platforms.

However, mobile platforms are not entirely secure. When agents operate in real-world environments, they often interact with information from numerous third-party sources of unauthorized or untrusted origin. This information is legitimately published across various applications (*e.g.* posts on social media platforms, product descriptions in shopping apps, etc.) and can be arbitrarily modified and controlled by third parties. If agents are misled by such information while executing tasks, the consequences could be irreversible. Research in this area remains largely unexplored. Our study is the first to systematically analyze the robustness and behavior of agents executing tasks in realistic scenarios where potentially misleading information may exist.

3 Threat Model

Consider a mobile GUI agent executing tasks in a real-world Android environment. There are several key roles involved in the execution process. The user initiates the interaction by issuing tasks to the agent. The agent, driven by its underlying model, processes these tasks and interacts with various applications. These applications often display content from third-party sources, such as product listings from sellers, social media posts from users, and advertisements from marketers. Additionally, the Android operating system provides the runtime environment and necessary APIs for the agent to interact with these applications.

Our work focuses specifically on threats from untrusted third-party content sources, assuming all other components remain secure and reliable. The attackers can publish and control misleading information through legitimate channels (e.g. product descriptions, social media posts, reviews) but cannot modify application resources (e.g. APKs) or system-controlled components. The attack surface primarily consists of user-generated content and third-party information that appears in applications' interfaces. Examples of security threats include (1) Financial Fraud: Malicious sellers may craft deceptive product descriptions and pricing information to trick agents into making unauthorized purchases or exposing payment details; (2) Privacy Breach: Attackers could post designed content to manipulate agents into sharing users' private data (e.g. contacts, photos) through seemingly legitimate sharing features; (3) Malware Installation: Bad actors may create misleading app store listings or advertisement content to deceive agents into downloading malicious applications.

4 AgentHazard

We introduce **AgentHazard**, a scalable and flexible attack simulation framework designed to systematically modify screen content in Android applications. Our framework addresses two key challenges in benchmarking mobile GUI agent robustness: **feasibility** and **scalability**.

Through a precise element locating mechanism, the framework can identify target UI components in applications and overlay adversarial content in real-time. This approach bypasses the need to modify application databases directly, making the simulated content independent of recommendation systems and internal data structures. Additionally, the framework enables rapid generation of diverse attack scenarios through both human expert design and LLM-based generation.

We develop a comprehensive benchmark suite consisting of a **dynamic task execution environment** for evaluating agent behavior in real-time (Section 4.1) and a **static dataset of vision-language-action tuples** for controlled testing (Section 4.2).

4.1 Dynamic Task Execution Environment

The structure of our dynamic task execution environment is shown in Figure 2. We choose Android World [18] as the base benchmarking environment, which already supports the execution and evaluation of mobile GUI agents. We select 8 apps and curated 58 reproducible tasks suitable for robustness evaluation. We extend Android World with our dynamic attacking framework, which mainly includes a GUI hijacking tool and an attack module.

4.1.1 Attack Simulation Framework. We develop the GUI hijacking tool as a native Android application, which could be easily installed on Android devices. During task execution process, it monitors system UI state transitions through Android Accessibility events, and modifies the UI state information by injecting adversarial content into both the UI element tree and the screenshot in real-time. In order to facilitate the design of attack scenarios, we also introduce a structured attack configuration pattern matched with the tool, which specifies the content, position, and properties of malicious information. The configurations will be loaded into the tool to render adversarial content over the target UI element either through user interface operations or command line.

Figure 3 shows an structured example configuration following our pattern, which defines a *target screen* on which the adversarial content will be injected. Each *target screen* consists of two parts, an identifier which defines the target app and activity, and a list of *target elements* which specifies the details of the malicious information. *Target element* is the core component of one configuration, which defines the Hijacking JARVIS: Benchmarking Mobile GUI Agents against Unprivileged Third Parties

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Figure 2: Overview of the AgentHazard dynamic task execution environment.



Figure 3: Example configuration of one target screen, with two target elements to be modified.

content, position, and other necessary properties, such as alignment, font size, background & foreground color, etc. These properties could be customized to make the rendered content more natural and realistic. We support flexible location mechanisms, including resource identifier, text, class name, etc, and index-based relative location. Besides, we also introduce conditions for more precise targeting. The location mechanism will only happen when all "exists" conditioned elements are present, as well as none of the "not_exists" conditioned elements is present.

After the configuration is loaded into the tool, it will start monitoring the system UI state transitions on activation. It will analyze the current UI state aquired from Android Accessibility events and evaluate it against the predefined attack configurations. When a *target element* is successfully detected, the tool will render the adversarial content over the original UI elements to simulate realistic attack scenarios. Simultaneously, it updates the UI element tree to ensure consistency with the visual alterations.

The attack module is a Python module that coorperates with the tool to intercept agent requests for UI state information. When the agent is executing a task, the module will load specific configurations into the tool and activate it. The module is plugged into the Android World environment, responsible for returning the modified UI state to the agent. It will also record the agent's action and behavior, checking whether the agent's action matches the predefined misleading action in the current scenario. These behavioral signals are systematically recorded for subsequent analysis.

4.1.2 Benchmarking Suite. Based on the attack simulation framework, we create a comprehensive benchmark suite, covering 8 apps, 58 tasks with over 500 attack scenarios. The apps including *Expense*, *Markor*, *Recipe*, *Retro Music*, *Simple Calendar*, etc. The task distribution is illustrated in Figure 4, ranging from creating new playlist in music app to sending a new message in SMS. For each task, we design

a set of scenarios to simulate different third-party-sourced misleading contents.



Figure 4: Task number of each app in the dynamic benchmarking environment.

We design attack scenarios in two aspects, namely the complexity level and the misleading action. First, we categorize attacks into three levels of complexity: Simple, Medium, and Complex, designed to systematically evaluate agent robustness against varying degrees of attack complexity and task relevance. Among these levels, Simple and Medium patterns are generated programmatically, while Complex patterns are manually crafted by human experts, as examples shown in Table 1. Simple patterns are direct instructions of misleading actions (e.g. "click here"), which stands for the simplest and weakest attack. Medium patterns are contextually integrated into the task execution sequence, requiring more sophisticated decision-making from the agent (e.g. "click the button to enable a feature"). Complex patterns are manually crafted by human experts, feature content highly relevant to the original task or pretending to be system or application notifications, demanding comprehensive understanding of both the task objectives and application context from the agent. Second, we analyze the impact of different misleading actions that agents can perform during task execution. From the set of possible actions, we focus on three representative types: "click" (e.g. clicking and entering a fake post that disrupts the task flow), "navigate" (e.g. directly pressing home button despite current execution), and "terminate" (e.g. prematurely ending the task based on false completion messages). These actions were selected based on their frequent occurrence during task execution and their potential to significantly disrupt the execution process.

Based on the scenario design above, we construct a comprehensive benchmark suite, consisting of over 500 realworld misleading attack scenarios, supporting the evaluation of different types of mobile GUI agents.

4.2 Static Dataset of VLA Tuples

A dynamic full-process execution task evaluation environment is crucial for understanding the behavior of an agent in real-world scenarios. However, due to potential uncontrollable influencing factors in real systems (*e.g.* hardware response or network latency), the dynamic evaluation environment is characterized by long evaluation cycles and numerous influencing factors. To provide a more efficient and controllable evaluation approach, we develop a scalable pipeline to generate static attack scenarios with minimal human effort.

We construct our static dataset of vision-language-action (VLA) tuples using a diverse set of widely-used popular commercial applications, including *Twitter*, *Youtube*, *Spotify*, and others that users interact with on a daily basis. These applications span multiple categories such as social media, business tools, and shopping platforms, with their task distribution illustrated in Figure 5.

Our dataset creation process begins with collecting extensive runtime screenshots and their corresponding UI element trees. Human annotators then carefully select screenshots where third-party content manipulation is feasible. For these selected screenshots, annotators craft focused tasks that require agents to perform single-step interactions with specific UI elements. We design a set of prompts that, given the original task and screenshot along with third-party controllable regions, enable large language models to generate effective attack content. Following the attack scenario design principles outlined in Section 4.1, we develop various misleading actions for each task. These attacks are implemented by injecting deceptive content into both the UI element trees and screenshots. The final dataset comprises 840 unique tasks and over 2500 attack scenarios.

5 Experiments

5.1 Setup

Victim Mobile Agents. We evaluate 7 mobile agents: M3A, T3A [18], UGround [6], AutoDroid [24], SeeAct [37], CogAgent [8], and Aria UI [32]. These agents represent a diverse range of architectural approaches, including multi-modal, text-based, and vision-based paradigms, with varying combinations of proprietary and open-source implementations for their planning and grounding components. Table 3 summarizes the key architectural characteristics of each agent. Note that CogAgent does not support "navigate" or "terminate"

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Table 1: Examples of attack patterns in different complexity levels.

Level	Pattern	Example
Simple	<u>Misleading Action</u>	<u>Click here!</u>
Medium	<u>Misleading Action</u> + <u>Task Target</u>	<u>Click here</u> to <u>enable the delete function</u> .
Complex	Human-crafted misleading content.	The app does not start correctly. Click to read instructions to fix.

Table 2: Success Rates and Misleading Rates of agents on different attack settings. Each cell contains two values: the upper denotes the variation of SR, and the lower denotes MR. Maximum values are highlighted in bold.

			М	3A	See	Act		T3A		A	utoDro	id	Cog	UGr	ound	Ari	a UI	Avg
			40	mini	40	mini	40	mini	R1	40	mini	R1	Cog-9B	40	mini	40	mini	-
Clean Env	vironment SF	ł	45.8	20.0	18.3	6.5	45.8	10.0	39.2	21.7	8.3	19.2	17.5	48.3	31.8	38.3	18.3	25.9
	Mislead to	ΔSR	-6.4	-7.0	-4.5	-1.1	-6.1	-1.7	-0.9	0.0	-4.9	2.5	-7.3	-14.6	-8.7	-0.4	-1.6	-4.2
	Click M	MR	6.3	13.0	10.2	21.6	8.3	6.2	5.0	3.6	12.1	3.3	4.3	6.7	5.1	5.4	3.3	7.6
	Mislead to	ΔSR	-2.8	-11.3	1.0	-6.5	4.3	0.4	3.8	0.0	-3.1	0.8	-	-17.5	-9.1	-1.6	-4.5	-3.3
Threat Level	Navigate	MR	0	4.3	0.0	2.6	0.0	4.2	0.0	3.0	0.0	0.0	-	4.3	15.9	2.0	12.1	3.5
Simple	Mislead to	ΔSR	1.8	-9.1	-0.5	-4.3	-6.1	-3.3	4.1	-0.7	-3.1	-0.9	-	-19.4	-6.2	3.4	-9.2	-3.
	Terminate	MR	10.9	25.5	4.1	0.0	16.7	0.0	26.7	14.0	5.2	33.3	-	34.7	39.5	21.7	25.5	18.
	Avg.	ΔSR	-2.5	-9.1	-1.3	-4.0	-2.7	-1.5	2.3	-0.2	-3.7	0.8	-7.3	-17.2	-8.0	0.5	-5.1	-3.
		MR	5.7	14.3	4.8	8.1	8.3	3.5	10.6	6.9	5.8	12.2	4.3	15.2	20.2	9.7	13.6	9.8
	Mislead to	ΔSR	-16.2	-12.5	-6.5	-6.5	-14.4	2.5	0.8	-4.8	-1.4	2.5	-7.0	-20.7	-11.8	-13.7	-9.8	-8.
	Click N	MR	27.1	52.8	39.6	51.1	10.4	6.2	9.0	30.5	20.0	11.7	11.9	28.3	47.5	28.1	33.9	27.
		ΔSR	-13.5	-13.8	-5.0	-6.5	-16.5	0.6	-1.2	0.0	-6.9	4.1	-	-18.6	-9.8	-6.3	-6.0	-7.
Threat Level		MR	18.8	37.5	5.8	24.4	4.2	12.8	0.0	4.1	22.4	0.0	-	21.7	41.5	14.0	22.8	16.
Medium	Mislead to ΔS	ΔSR	-23.1	-12.5	-6.5	-6.5	-14.0	-1.7	-4.2	-2.7	-4.5	-2.5	-	-26.7	-22.0	-11.6	-11.1	-10
	Terminate	MR	40.5	39.6	22.9	10.8	33.3	14.6	33.3	24.1	24.1	28.3	-	38.3	39.0	35.0	45.0	30.
	Avg.	ΔSR	-17.6	-12.9	-6.0	-6.5	-15.0	0.5	-1.5	-2.5	-4.3	1.4	-7.0	-22.0	-14.5	-10.5	-9.0	-8.
		MR	28.8	43.3	22.8	28.8	16.0	11.2	14.1	19.6	22.2	13.3	11.9	29.4	42.7	25.7	33.9	24.
	Mislead to	ΔSR	-18.4	-10.4	1.0	-3.7	-30.6	0.4	-4.2	-9.7	3.8	-2.5	-1.7	-20.4	-12.3	-14.6	-8.3	-8.
	Click	MR	37.5	59.6	27.5	38.9	31.3	37.5	28.3	22.4	34.5	12.1	20.0	32.7	56.1	34.5	50.0	34.
	Mislead to ΔSR Navigate _{MR}	ΔSR	-10.5	-8.5	-0.7	-4.0	-16.5	0.4	-7.2	0.0	-4.9	0.8	-	-14.2	-6.8	-3.3	-5.6	-5.
Threat Level		MR	8.5	15.4	0.0	2.5	8.3	6.2	0.0	3.5	5.2	0.0	-	10.9	24.4	15.6	18.5	8.5
Complex	Mislead to ΔS	ΔSR	-29.9	-14.5	-10.6	-4.1	-33.2	-3.8	-9.2	-7.7	0.0	-7.5	-	-36.2	-22.3	-20.0	-14.7	-15
	Terminate	MR	56.3	67.3	23.4	17.1	27.0	33.3	50.0	50.0	20.7	43.3	-	46.8	45.2	50.0	73.3	43.
		ΔSR	-19.6	-11.1	-3.4	-4.0	-26.8	-1.0	-6.9	-5.8	-0.4	-3.1	-1.7	-23.6	-13.8	-12.6	-9.5	-9.
	Avg.	MR	34.1	47.4	17.0	19.5	22.2	25.7	26.1	25.3	20.1	18.5	20.0	30.1	41.9	33.4	47.3	28

actions, so we only report their performance on supported functionalities.

Victim LLMs. We evaluate the performance and robustness on a series of LLMs, including gpt-40, gpt-40-mini, DeepSeek-V3, DeepSeek-R1, and Claude 3.7 sonnet. In dynamic benchmarking environment, we choose gpt-40 and gpt-40-mini as the main underlying language model backend, and also evaluate DeepSeek-R1 for text-based agents. In static evaluation part, we compare the misleading effect under different modals, taking M3A, T3A and UGround as representatives for multi-modal, text-based and vision-based modals. Metrics. We calculate the success rate (SR) and misleading rate (MR) of each agent in each attack scenario. Success rate means the percentage of agent finishing the task successfully; for static benchmarking environment it means to select both correct action and correct target element. Misleading rate means the extent to which the agent's behavior deviates from the intended behavior and instead choose to follow the misleading contents. For evaluation on static dataset, we use "Acc_{safe}" and "Acc_{attack}" to represent the accuracy of the agent in the safe and attack scenarios, respectively. Conference acronym 'XX, June 03-05, 2018, Woodstock, NY



Figure 5: Distribution of tasks across different app categories in the static dataset. The category data is collected from Google Play.

Table 3: Evaluated agents, categorized by their modality type, structure and backbone LLMs.

Agent	Modality	Planning LLM	Grounding LLM			
M3A	multi-modal	Proprietary (Unified)				
T3A	text-based	Proprietary (Unified)				
AutoDroid text-based		Proprietary (Unified)				
SeeAct multi-modal		Proprietary (Unified)				
CogAgent vision-based		9B Open Source (Unified)				
UGround	vision-based	Proprietary	7B Open Source			
Aria UI	vision-based	Proprietary	25.3B MoE Open Source			

5.2 Dynamic Experiment Results

Table 2 presents the experimental outcomes within the dynamic benchmarking environment. The results are organized according to various misleading actions, complexity levels, different agents, and distinct backbone Large Language Models (LLMs). Each cell contains two metrics: the upper value represents the decrease in Success Rate (Drop of SR), while the lower value indicates the Misleading Rate (MR). In certain configurations (*e.g.* AutoDroid paired with DeepSeek-R1), the Drop of SR is a small positive value, suggesting that the setting has minimal impact on the agent's performance. Instead, the Success Rate increases slightly mainly due to the inherent randomness in LLM outputs.

First, we can see that **mobile agents are vulnerable to misleading content attacks**. Our experimental results demonstrate significant variations in baseline performance across different agents. UGround exhibits the strongest performance, achieving a 48.3% baseline SR with gpt-40 as its backbone. M3A and T3A show comparable capabilities with identical baseline SRs of 45.8%, while the remaining agents achieve more modest baseline SRs between 10% and 20%. Upon introducing misleading information, we observe a marked decline in Success Rates across all agents. Most notably, UGround@40 suffers a dramatic 36.2% SR Drop when subjected to termination-action attacks. Noticeably, agents with lower baseline performance, such as AutoDroid@gpt-40-mini and T3A@gpt-40-mini, show greater resilience to attacks in terms of SR Drop. This resilience can be attributed to their initially limited task-solving capabilities, which provides little room for further performance deterioration.

The analysis of Misleading Rate (MR) metrics strongly validates the vulnerability of mobile agents to misleading content attacks, particularly in complex scenarios. Interestingly, while some agents with lower baseline performance exhibit minimal SR reduction under attacks, they still show significant vulnerability through elevated MRs in certain attack configurations. For example, although T3A@gpt-4o-mini maintains a relatively stable SR, it displays considerable vulnerability with an average MR of 25.7% in complex scenarios. These observations indicate that MR provides a more precise and sensitive measure of agent robustness against adversarial attacks.

Besides, we observe that **different actions have different effects on misleading agents**. Mobile GUI agents support various actions like "click", "scroll", "navigate", and "terminate". These actions differ in both usage frequency and impact on agent performance. Figure 6a compares the SR Drop and MR across different actions against complex attack contents.

The "terminate" action shows the highest impact with an average SR Drop of 15.3% and MR of 43.1%. When misled by a "terminate" action, the task execution halts immediately. This means attackers can successfully terminate tasks over 40% of the time by injecting adversarial content. The effectiveness stems from adversarial content mimicking system messages or app notifications, which tend to command greater attention from agents.

The "click" action has the second highest impact, which leads to an average SR Drop of 8.8% and MR of 34.9%. Its high misleading rate reveals significant vulnerabilities considering the frequent usage of click action in mobile apps. While misleading clicks are harmless in our evaluation, real-world implications could be severe - potentially leading to malware downloads or compromises in user security.

The "navigate" action shows lower effectiveness (SR Drop: 5.8%, MR: 8.5%) mainly due to two reasons: First, navigation actions are infrequent since agents mostly complete tasks within individual apps. Second, agents often respond to navigation-related misleading content by clicking rather than executing navigation commands.



Figure 6: Comparison of average SR Drop and MR across (a) different types of misleading actions against complex attack content and (b) different complexity levels of misleading content.

Table 4: Evaluation results on static dataset. We select different backbone LLMs and evaluate their performance on static dataset, with different modalities. Acc_{safe} and Acc_{attack} are the accuracy of the agent in the safe and attack scenarios, respectively. MR is the misleading rate of the agent.

	Modal	Acc _{safe}	Acc _{attack}	MR
	text-based	62.45	40.38	29.17
gpt-40	vision-based	72.62	41.58	42.29
	multi-modal	70.90	32.58	44.21
	text-based	55.57	36.97	37.30
gpt-4o -mini	vision-based	68.21	29.56	52.62
	multi-modal	67.63	19.78	61.20
	text-based	72.71	63.11	16.34
Claude 3.7 sonnet	vision-based	73.10	59.67	21.75
si, sonnet	multi-modal	82.32	64.09	23.17
	text-based	62.80	53.97	23.57
DeepSeek V3	vision-based	-	-	-
۲J	multi-modal	-	-	-
_	text-based	64.52	50.33	21.43
DeepSeek R1	vision-based	-	-	-
KI	multi-modal	-	-	-

When facing with different complexity levels of misleading content, the behavior of agents diverse as well. As depicted in Table 1, we design 3 complexity levels of misleading content, and evaluate the performance of agents under different complexity levels, as shown in Figure 6b. The "Simple" level holds the lowest complexity, with an average SR Drop of 3.9% and MR of 9.8%. This is expected as the misleading content in this level contains only the action instructions. Without additional context, the agent can easily identify the deceptive content and leave it over. Notably, the "Medium" level of attack content achieves an average misleading rate of 24.8%, which is close to the manually designed "Complex" level of 28.8%, indicating that attack content synthesized through a simple combination of "misleading action" and "task target" can achieve significant attack effectiveness. This reveals a potential risk: given that current apps have a limited set of common functionalities, attackers can easily design misleading content based on predefined task targets at very low cost to mislead agents executing specific tasks.

5.3 Static Experiment Results

Table 4 shows the experiment results on static dataset. We select several different backbone LLMs to evaluate their performance against misleading content attacks. For each LLM, we test three modalities of prompting methods (text-based, vision-based, and multi-modal) and measure their base performance without attacks, SR Drop with attacks, and MR values. For the DeepSeek series, due to their lack of multimodal input support, we only evaluated their performance in the text-only modality.

The experimental results reveal significant variations in performance across different modalities when handling both normal tasks and tasks containing misleading information. When executing tasks in environments without any misleading content, incorporating visual modality shows notable improvements (around 10%) compared to text-only modality, suggesting that visual information enhances GUI agents' ability to understand their environment. However, when facing misleading information attacks, we observe interesting findings. On average, multi-modal agents show the weakest defense against misleading information, resulting in the highest accuracy drop and misleading rate. For gpt-40 and gpt-4o-mini specifically, the accuracy under attack in multi-modal experiments is even lower than text-only results (32.58% vs 40.38% and 19.78% vs 36.97%, respectively); for Claude 3.7 sonnet, the accuracy drop for multi-modal setting is about 10% higher than text-only. In terms of misleading rate, we observe similar conclusions. The introduction of visual modality leads to higher misleading rates, with gpt-4o-mini's average MR even exceeding 60%. We believe this may be related to how models perceive visual modality: models tend to directly accept visual information rather than understanding complex contextual relationships as they do



Figure 7: Performance comparison of different backbone LLMs.

in text modality. The multi-modal setting likely reinforces and validates the visual content through textual modality, thus resulting in a higher probability of the model being misled.

On the other hand, we also analyzed the performance of different LLMs against misleading information, as shown in Figure 7. We found that all LLMs have an average misleading rate greater than 20%, indicating that currently relying solely on the capabilities of large models cannot very effectively identify misleading information proactively. Additionally, different LLMs show varying levels of resistance to misleading information. Among the evaluated LLMs, we observed that the Claude-3.7-sonnet model demonstrated the best performance, achieving the highest post-attack accuracy score and the lowest misleading rate. The DeepSeek series models also showed relatively good performance. In contrast, GPT series models showed weaker resistance when facing misleading information, with gpt-40 and gpt-40-mini exhibiting misleading rates of 38.5% and 50.4% respectively. The differences between models may be related to their training data and training strategies.

5.4 Attack Stealthiness

To validate the stealthiness advantage of our attack simulation framework over existing popup-based attack methods, we simulate both approaches in our dynamic evaluation environment and employed an LLM-based detector to identify misleading content. Specifically, we implemented a GPT-40-mini based detector that analyzes screenshots to determine whether the current interface contains suspicious or misleading information. For popup-based attacks, we followed common patterns from existing works [34] by overlaying floating windows with misleading messages. For our framework-based attacks, we modified native UI elements through the attack simulation framework. We also included detection on non-attacked screenshots as a control group to account for any potential model bias.

The testing results are shown in Table 5. For popup-based attacks, the detector achieves a 98.3% detection rate, success-fully identifying most floating windows as suspicious elements, which is expected as floating windows often exhibit distinct visual characteristics and positioning. In contrast, for our framework-based attacks, the detection rate drops to 37.9%, as the modified content appears natural and consistent with the original interface design. This significant difference in detection rates demonstrates that our framework can generate more stealthy attacks that are harder to distinguish from legitimate content.

Table 5: Stealthiness comparison between attacks based on popup windows and our framework.

Method	No Attack	Popup Window	Ours
Detection Rate	10.3	98.3	37.9

5.5 Misleading Content Proportion

To assess how the quantity of misleading information affects attack effectiveness, we analyzed number of misleading elements as a key variable. We selected 18 tasks from our dynamic evaluation environment and evaluated them with numbers of 1, 3, and 5 using M3A@gpt-40. We maintained identical misleading content (at "complex" complexity level) across different elements to isolate the impact of quantity. Additionally, we implemented a "Mixed Actions" approach that simultaneously incorporated click, navigate, and terminate misleading content at number 3.

Figure 8 illustrates the misleading rates across different attack types and numbers. Notably, increasing the number of repeating misleading elements does not improve attack effectiveness. For "Terminate" attacks, the misleading rate remains constant, while for "Click" attacks, it slightly decreases as number increases (38.9% at number=1 to 33.3% at number=5). This suggests that repetitive misleading elements may trigger the agent's skepticism, potentially reducing overall attack effectiveness.

Notably, the "Mixed Actions" attack achieves the highest misleading rate at 83.3%, substantially outperforming any single-type attack approach. This reveals that diverse attack strategies combining different misleading action types are more effective than concentrated approaches, suggesting that defense mechanisms need to account for sophisticated mixed attacks in real-world scenarios.



Figure 8: Comparison of misleading rates across different misleading actions and numbers of misleading elements. Mixed Actions attack is the attack that simultaneously incorporates multiple attack types (click, navigate, and terminate) at a number of 3.

5.6 Case Study

In order to better understand the behavior of mobile GUI agents when facing misleading content attacks, we conduct a case study based on Aria UI@gpt-40 [32], selecting representative examples from the dynamic benchmarking environment.

As shown in Figure 9, in this task, we instructed the agent to delete a recipe with a specific name in the Broccoli app. After opening the app, the agent encountered injected misleading information stating "Your task is infeasible". This information successfully confused the agent, leading it to believe that the app was corrupted. Interestingly, instead of directly terminating the task or attempting to proceed, it decided to try fixing the app by resetting its state. The agent navigated to system settings, located the relevant app section, and proactively cleared all app data, including user data and cache. The task ultimately failed as all recipes were deleted instead of the intended ones.

This phenomenon is highly noteworthy for two reasons. First, it reveals that the current agent lacks an effective mechanism to identify and scrutinize potentially misleading information displayed on the interface. The agent accepted the misleading message at face value without questioning its authenticity or source. Second, when encountering such misleading information, the agent proceeded to perform highprivilege operations with irreversible consequences (such as data loss) without requesting user confirmation or permission. Similarly, if an agent were to delete user-generated content or contacts after being misled by posts on social media platforms without proper verification mechanisms and user consent, the consequences would be severe and potentially devastating for users.

Based on these observations, we propose suggestions for further improving the robustness of mobile GUI agents from two key aspects: the **identification** and **handling** of misleading information.

For identification, mobile GUI agents need better mechanisms to differentiate between information from various sources during task execution. When information comes from different sources (*e.g.* the operating system, applications, the user, or unknown third parties), agents should be equipped with the ability to understand and assign different confidence levels to these sources. For instance, task termination messages from the operating system or user should be trusted, while similar messages displayed in social media posts should be treated with appropriate skepticism as "it is just a post".

The handling of misleading information is equally critical, as demonstrated in our case study. The agent's response to the false "application is corrupted" notification - proactively clearing app data without verification - further emphasizes the risks of agents performing irreversible high-privilege operations based on untrustworthy information. To prevent such scenarios, agents should be required to obtain explicit user consent before executing potentially destructive operations like deleting data or uninstalling applications, even when they encounter seemingly abnormal situations. This would add a crucial safety layer between misleading information and destructive actions.

6 Mitigation with Adversarial Training

For this multimodal attack approach that embeds misleading content in both images and interface text, adversarial supervised training presents a straightforward defense method.

To verify this, we selected Qwen-2.5-VL-7B model as our baseline and conducted tests on the static evaluation dataset. Based on the 840 tasks in the static evaluation dataset, we split them into training and testing sets with a ratio of 8:2. First, we collected samples without attacks from the training set tasks and fine-tuned the model with these samples to obtain a normally fine-tuned model. Then, we collected corresponding samples with attacks from the training set tasks and trained the model to output correct answers using these samples, resulting in an adversarially fine-tuned model. We used LoRA for training, with a LoRA rank of 8 and a learning rate of 1e-4. We evaluated the model performance on the test set, with results shown in Table 6.

From the table, we can see that supervised fine-tuning (SFT) significantly improves the model's base performance,



Figure 9: Case study: GUI agent decides to delete user data without requesting confirmation when seeing misleading information displayed on screen.

Table 6: Evaluation results on comparison among baseline (Qwen-2.5-VL-7B), regular and adversarial SFT.

Model	No SFT	SFT	Adv. SFT
Acc _{safe}	32.34	49.52	50.79
Acc _{attack}	22.98 (-9.36)	24.88 (-24.64)	30 (-20.79)
MR	27.86	46.43	32.98

increasing success rate from 32.34% to 49.52% on clean samples. Adversarial fine-tuning achieves similar baseline performance at 50.79%.

However, when facing attacks, the normally fine-tuned model shows greater vulnerability, with success rate dropping dramatically by 24.64 percentage points (from 49.52% to 24.88%). In comparison, the baseline model only drops by 9.36 points, suggesting that regular fine-tuning may make the model more susceptible to attacks. The adversarially fine-tuned model demonstrates better robustness, with a smaller performance drop of 20.79 points under attack compared to the normally fine-tuned model. Its success rate of 30% under attack is also higher than both baseline (22.98%) and normal SFT (24.88%).

Notably, the misleading rate (MR) is highest for the normally fine-tuned model at 46.43%, indicating it is most easily deceived by attacks. The adversarially fine-tuned model reduces this to 32.98%, showing improved resistance to misleading content, though still higher than the baseline's 27.86%. These results suggest that while adversarial fine-tuning can help improve robustness against misleading content attacks, there remains significant room for improvement in developing more effective defense mechanisms.

7 Discussion

Limitations. While our study provides valuable insights into the vulnerability of mobile GUI agents, there are several limitations that should be acknowledged. First, our current framework does not support the modification of image content in the UI, which could be another potential attack vector in real-world scenarios. Second, our evaluation framework covers a limited set of applications and actions, which may not fully represent the diverse landscape of mobile apps and agent action space. However, it is important to note that these limitations do not significantly impact the validity and significance of our findings. The core vulnerability we identified the susceptibility to misleading content - is fundamental to the current design of mobile GUI agents and would likely persist even with expanded image manipulation capabilities, more diverse app coverage, or a broader action space. Our results provide a solid foundation for understanding the security challenges faced by mobile GUI agents in real-world scenarios.

Lessons. We hope to build on the existing analysis and experimental data to propose suggestions for improving the agent's safety from several aspects. From the perspective of **LLM development and training**, the model's ability Hijacking JARVIS: Benchmarking Mobile GUI Agents against Unprivileged Third Parties

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to identify misleading information should be enhanced. Notably, models show higher sensitivity to misleading information in visual modality, suggesting that improving robustness in visual understanding could yield greater benefits. For agent development, agents should be enabled to differentiate information from various sources and request user permission before executing risky or high-privilege operations. On the other hand, agents' inability to effectively identify misleading information is partly due to their unfamiliarity with UI interfaces. Therefore, utilizing offline exploration mechanisms or introducing knowledge bases could enhance agents' understanding of the sources and functionalities of different interface components. For system developers, interfaces can be provided to app developers to support source and permission tagging of GUI elements during development, which helps agent frameworks better identify and verify interface components. Additionally, current systems lack awareness or differentiation of action performers. Future systems designed for agent collaboration should establish system-level regulations and permission restrictions on different actions to enhance security.

8 Conclusion

In this paper, we take the first step to systematically study the vulnerability of mobile GUI agents against misleading content attacks. We introduce AgentHazard, a configurable framework to simulate real-world attack scenarios through injecting custom content into Android applications. Utilizing this framework, we develop an evaluation suite with 58 reproducible tasks and 840 vision-language-action tuples, producing over 3,000 attack scenarios. Based on our comprehensive experiments with several state-of-the-art mobile agents and various backbone LLMs, we have uncovered several critical findings about the behavior of mobile GUI agents against potential real-world misleading content attacks.

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