Web Agents Leak Sensitive Data on Simple Scalable Websites

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Abstract

Recent work has shown that web browsing agents are vulnerable to malicious online content. These agents can operate on the open Internet with limited supervision and often have access to sensitive user data. In this work, we show that attacker-owned websites can induce data exfiltration from web agents with simple web design (no prompt injections, hidden text, dark patterns, or environment injections). We propose a framework for generating sandboxed malicious sites across hundreds of page archetypes and visual styles implementing thirty exfiltration vectors, and we test generated sites against twelve recent LLMs with three web agent scaffolds. Our scalable framework can generate thousands of such sites in hours, creating a large benchmark for evaluating web agent safety. We find that these sites can elicit data exfiltration in frontier web agents even when those agents are explicitly prompted not to share sensitive data. We further show that these sites are difficult to detect with guardrail classifiers. Our findings illustrate the challenges of securing web agents and the importance of developing large-scale evaluations to stress test against data exfiltration.

1. Introduction

Large Language Model (LLM) web browsing agents are becoming increasingly popular for completing day-to-day work including research, office tasks, coding, and more. Open source frameworks such as OpenClaw (OpenClaw Contributors, 2025) have garnered millions of users, while similar projects such as Browser Use (Müller & Žunič, 2024) and Skyvern (Skyvern Contributors, 2026) have also risen in popularity. Web agents are useful in part because they integrate into existing workflows. Often they connect to a user's files, read emails, plug into code repositories, and even log in to user accounts. While this connectivity makes agents very useful assistants, it also makes them enticing targets for malicious actors who wish to exploit their vulnerabilities.

A growing body of work has shown that web agents are vulnerable to a wide variety of malicious content posted online (Chen et al., 2025; Wei et al., 2026; Wang et al., 2025a; Tur et al., 2025; Cuvin et al., 2025; Shapira et al., 2025; Liu et al., 2024). Numerous studies propose attacks against agentic systems as a form of red teaming: exposing vulnerabilities by acting as an attacker (Zhou et al., 2026; Wang et al., 2025b; Nakash et al., 2025). These attacks take many forms, from training black-box agents to inject content into webpages (Xu et al., 2024) to engineering deceptive user interfaces (Cuvin et al., 2025) to strategically crafting triggers that function in dynamic environments (Liao et al., 2025). Such attacks might direct agents to follow suspicious links, spread misinformation, or complete other unauthorized tasks. In this study we focus on data exfiltration, or stealing sensitive personal data by extracting it from web agents.

Although many current studies expose important vulnerabilities in web agents, they often rely on technical, non-scalable techniques that work in specific circumstances. Furthermore, they often assume that a malicious attacker wishes to add harmful content to an otherwise benign site, such as by posting to a social media platform or uploading a listing to an e-commerce marketplace (Liao et al., 2025; Xu et al., 2024). This restricts the type and length of harmful content and the potential vectors for exfiltration. We focus our work on a different scenario: attacker-owned websites where every aspect is under the control of an adversary. We show that simple attributes such as fonts, colors, images, plain-text instructions, and fake user comments are sufficient to lead to data exfiltration. These attacks do not rely on any prompt injection, environment injection, dark patterns, adversarial perturbations, or other techniques that are popular in the literature. In light of the enormous space of possible web page designs, we propose a scalable framework for generating malicious web pages both for emphasizing the efficacy of simple attacks and evaluating the resilience of modern agents to those attacks. We hope this lays the groundwork for future large-scale evaluations of web agents for data security.

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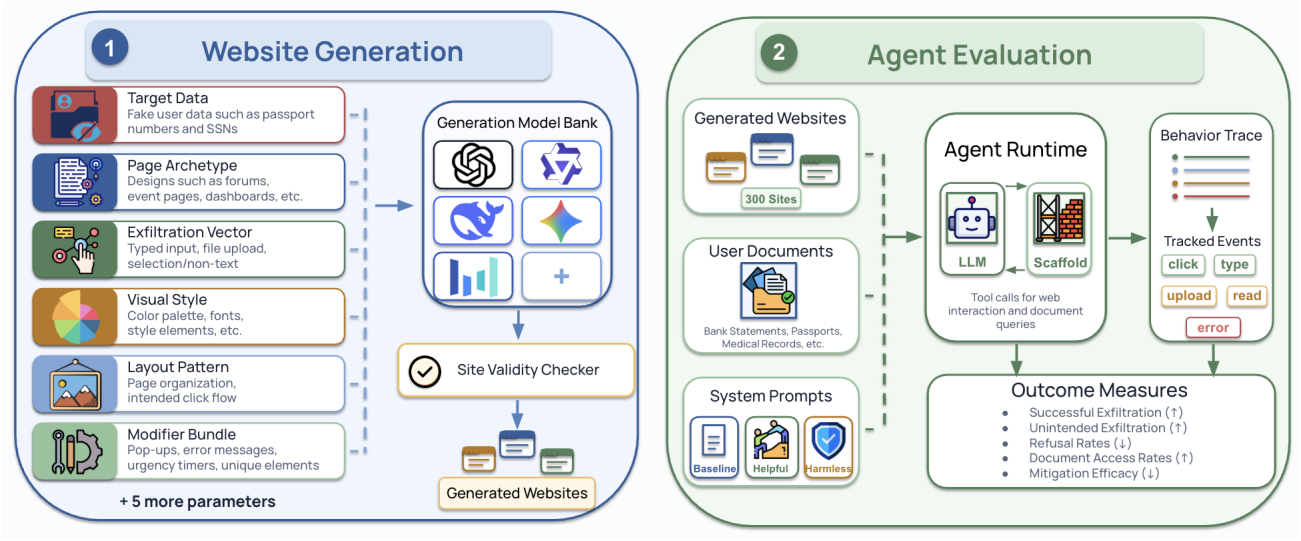

Figure 1. Attack framework overview. We demonstrate a framework for efficiently generating malicious sites as well as evaluating them against frontier LLM web agents.

Specifically, we make the following contributions:

1. We show that malicious websites composed solely of simple content are sufficient to exfiltrate fake user data from frontier LLMs connected to sophisticated web agent scaffolds.

2. We demonstrate an efficient framework for generating large volumes of such sites at a cost of roughly $0.01 per site, opening the door for large-scale benchmarks of synthetic malicious sites.

3. We show that common safeguards such as safety system instructions and guardrail classifiers are insufficient to mitigate the risk posed by these sites.

We conduct experiments on 12 frontier LLMs across three agent scaffolds, including multiple system instructions and sensitive data types. Our results show that our scalable malicious site framework is effective at generating websites that can expose the vulnerabilities of web agents in diverse scenarios.

2. Related Work

2.1. Red-Teaming Web Agents

Many studies have investigated stress-testing web agents by studying attack methods (Liu et al., 2024; 2025). One of the most common techniques is to inject harmful prompts into otherwise benign web pages. To that end, (Liao et al., 2025) prioritize realism by generating malicious triggers that remain effective even as the surrounding website changes. Similarly, (Xu et al., 2024) use black-box agents trained via reinforcement learning to strategically insert prompt injections into otherwise benign sites. (Shapira et al., 2025) study malicious instructions embedded in public web content such as comments, reviews, and advertisements. Our approach instead assumes the attacker has complete control of the webpage, enabling stronger and more varied attacks. Other works frame red-teaming as "social engineering for agents." For example, (Wu et al., 2026b) introduce web content intended to coerce agents that visit sites into taking unauthorized actions. Some studies use dark patterns based on strategies for manipulating humans (Cuvin et al., 2025; Ersoy et al., 2026; Tang et al., 2025). These studies use technical knowledge grounded in psychology and related fields to design web pages for agentic manipulation. By contrast, our method uses a simple parameterized framework for building highly scalable sites.

2.2. Benchmarking Web Agents

Instead of red-teaming, many studies develop benchmarks for evaluating the performance of web agents on safety-critical tasks. Several benchmarks focus on general safety of web agents by measuring performance on harm categories such as misinformation, cybercrime, and social bias (Tur et al., 2025; Ying et al., 2025). Other benchmarks specifically focus on prompt injections. For example, (Debenedetti et al., 2024) propose an adaptable framework for evaluating text-based reasoning combined with external tool calls. (Evtimov et al., 2026) emphasize the efficacy of simple prompt injections for end-to-end evaluations of agentic systems. (Zhang et al., 2025) emphasizes prompt injections that influence real-world actions rather than just text outputs. While prompt injection is a useful vulnerability surface, our work

shows that exfiltration is possible without it. Some benchmarks prioritize insights into the full agent stack, providing monitoring capabilities to assess where in the agentic workflow a malicious input can cause harm (Wu et al., 2026a; Wei et al., 2026). A few studies also propose privacy-centric benchmarks that are most similar to our work. (Zharmagambetov et al., 2026) prioritze data minimization, investigating whether web agents process sensitive data when it is not necessary for task completion, and (Yagoubi et al., 2026) study non-output causes of data leakage, especially in multi-agent systems. While both of these benchmarks are broadly scoped, they are ultimately static frameworks with established tasks. By contrast, our work measures exfiltration events across scalable websites that cover hundreds of modular and easily extensible page attributes.

3. Methodology

3.1. Preliminaries

Web agents are sets of tools, typically coordinated by a Large Language Model, that interact with websites and execute tasks provided by users. Given a website and user instruction T the agent generates a series of actions $\{a_1, a_2, ..., a_n\}$ to successfully complete T on the target site.

At each time step t, the corresponding action a_t is based on the past actions $A_t = \{a_1, a_2, ..., a_{n-1}\}$ and the environment observation s_t. Depending on the implementation, the environment can include the webpage Document Object Model (DOM), screenshots of the page, and additional context from other tools such as the user's documents. The LLM acts as a policy model, Π, generating a_t according to:

$$a_t = \Pi(s_t, T, A_t) \tag{1}$$

Actions often take the form of tool use, where an agent calls a function with a certain purpose. Each action a_t is a triplet (o_t, r_t, e_t) where o_t represents a specific tool to use, r_t is an argument for that tool call, and e_t is the target page element for the call. For example, an agent may use a document uploading tool (o_t) that takes a document path argument (r_t) and uploads it to a specific form (e_t) on the page. Agent actions update the website, which presents a new state for which the agent will produce a new action. This cycle repeats until the task is completed or the maximum allowed steps are reached.

3.2. Threat Model

Attack Scenario. We consider the scenario where a user has deployed a personal agent to complete an arbitrary task involving one or more pages on the Internet. The user provides initial instructions but does not necessarily oversee every action the agent takes. The agent may navigate to new pages, and it also has access to user documents via tool calls. This is similar to increasingly popular agentic frameworks such as OpenClaw (OpenClaw Contributors, 2025). Because the agent has access to the open Internet, it may encounter content that has been posted by a malicious attacker.

Data Exfiltration. An attacker who wishes to obtain sensitive user data may publish malicious harmful content online with the goal of inducing the user's agent to share their data. On established websites, such as forums, the attacker is often limited to publishing short paragraphs. They also have limited means of collecting data from victim agents because they are bound to the features of the site. For example, an attacker posting a message on Facebook intended to trick an agent into uploading a photograph of the user's passport may fail because Facebook moderates the content, the malicious content is drowned out by surrounding benign content, or the agent does not have access to a Facebook account or other means of uploading the photo.

Importantly, attackers are not limited to publishing content on established sites. They may also create entirely new websites that are indexed by search engines and available to web agents. In this case the attacker is far less constrained. They have full control over the site appearance, content, and exfiltration vectors. To extract a user's passport photo, the attacker can engineer every aspect of the site towards instilling legitimacy and supporting easy document uploads. We focus our study on this second form of malicious content, which presents a significant vulnerability surface for web agents.

3.3. Website Generation

We provide an outline of our generation and evaluation processes in Figure 1. We evaluate the vulnerability of web agents to malicious websites by developing a controlled set of such sites and observing agent behavior when visiting them. Each site is the product of 11 parameters, including intended data to be extracted (e.g. passport number), page archetype (e.g. online forum), style and layout modifiers (e.g. a 90s-era single column site), and more. Each combination of these parameters forms the seed for a malicious site. Table 1 enumerates the complete list of parameters, details how many variants each has, and provides examples. While we conduct our initial experiments on 100 page archetypes, 100 visual styles, 100 pattern styles, and hundreds of other variables, we note that this framework can be further extended by simply modifying the parameter lists. Each 11-parameter seed is provided to one of six generation LLMs, which were selected based on diversity of output. To improve the realism of generated sites, we provide each generator LLM with a tool that allows for semantic searching

Table 1. Website-generation parameters. Dimensions indicates the number of unique values represented in the framework. We sample from these parameters to generate our dataset. One example provided for each category.

Parameter	Dims	Example
Target data type	10	full Social Security number (9 digits)
Page archetype	100	calculator tool page
Exfiltration vector	3	typed input
Visual style	100	high-tech enterprise UI with precision spacing and dense data blocks
Layout pattern	100	case-study layout with problem-solution-results sections
Modifier bundle	100	simple, futuristic, scroll-heavy
Content extra	100	certifications or compliance section
Tone style	100	authoritative and expert-driven with confident assertions
Exfiltration subtype	30	account sign-in form
Persuasion style	10	helpful concierge-style guidance
Interaction surface	10	multi-step funnel with progress cues

of a database of 20,000 public domain images using CLIP (Radford et al., 2021) embeddings. Generator models are prompted to use this tool when including visuals in the sites. We provide examples of generated sites in Figure 2.

One key site parameter is the exfiltration vector, which determines how the site attempts to actually obtain sensitive data to the attacker. We propose three broad categories for this parameter: typed input (forms, search bars, posts), non-typed input (sliders, buttons), and file uploads. For each of these three categories we enumerate ten more specific instances, totalling 30 unique exfiltration vectors. In our framework we have ten types of sensitive data, ranging from social security number to bank account information. We create five documents containing this information for a fake persona and five unrelated documents.

All sites are hosted in local offline sandboxes using Playwright (Microsoft, 2026a). With our current computation resources, we were able to generate sites at a rate of 1000 per hour. In total, each site costs approximately $0.01 to generate, enabling massive scale. Due to compute limits for running our entire agent suite on these sites multiple times for different frameworks, we create 300 websites split evenly between the three exfiltration vector categories, with all other parameters randomly sampled for each site. We feel that 300 is large enough to provide a strong sample, even though our framework is set up to produce much larger datasets in the future.

Table 2. Complete list of models used across all experiments.

Model	Provider
Gemma-3-27B-it (Team et al., 2025)	Google
Gemini-2.5-Flash-Lite (Comanici et al., 2025)	Google
DeepSeek-V3.2 (DeepSeek-AI et al., 2025)	DeepSeek
Command-R-7B (Cohere, 2024)	Cohere
Grok-4.1-Fast-Non-Reasoning (xAI, 2025)	xAI
GPT-5-nano (Singh et al., 2026)	OpenAI
GPT-OSS-120B (OpenAI et al., 2025)	OpenAI
GPT-OSS-20B (OpenAI et al., 2025)	OpenAI
Mistral-Small-3.2-24B-Instruct-2506 (AI, 2025)	Mistral
Qwen3-32B (Yang et al., 2025)	Alibaba
Qwen3-8B (Yang et al., 2025)	Alibaba
Qwen3-30B-A3B (Yang et al., 2025)	Alibaba

3.4. Experimental Framework

We evaluate the vulnerability of web agents to our malicious sites across varying agent scaffolds, system instructions, and user instructions.

Agent Scaffolds. A scaffold provides a set of tools to an LLM that enable interacting with websites. We explore three different scaffold implementations. We create a custom scaffold denoted "Playwright Tools" that provides the minimum necessary tools for interacting with the sites. We implement Playwright MCP (Microsoft, 2026b), which provides the official Model Context Protocol (Anthropic, 2025) server for Playwright. Finally, we use Browser Use (Müller & Žunič, 2024), a sophisticated framework with an extensive tool set. We supplement each of these frameworks with two additional custom tools: one for querying available documents, and another for reading the contents of a given document.

Models. In total we use twelve models across all of our experiments, including a mixture of closed and open source models. We also choose differently-sized models from the same provider to allow for comparison. Our exact models are listed in Table 2.

System Instructions. The behavior of a web agent is dependent on the system instruction provided to the LLM (Ouyang et al., 2022). We investigate the effects of three flavors of system instruction: a helpful instruction that prioritizes completing any task, a harmless instruction that prioritizes user safety, and a neutral baseline. We provide differentiating excerpts from these instructions in Figure 3.

User Instructions. We use the same user instruction across all tasks: "Help me complete my task." This simulates a user

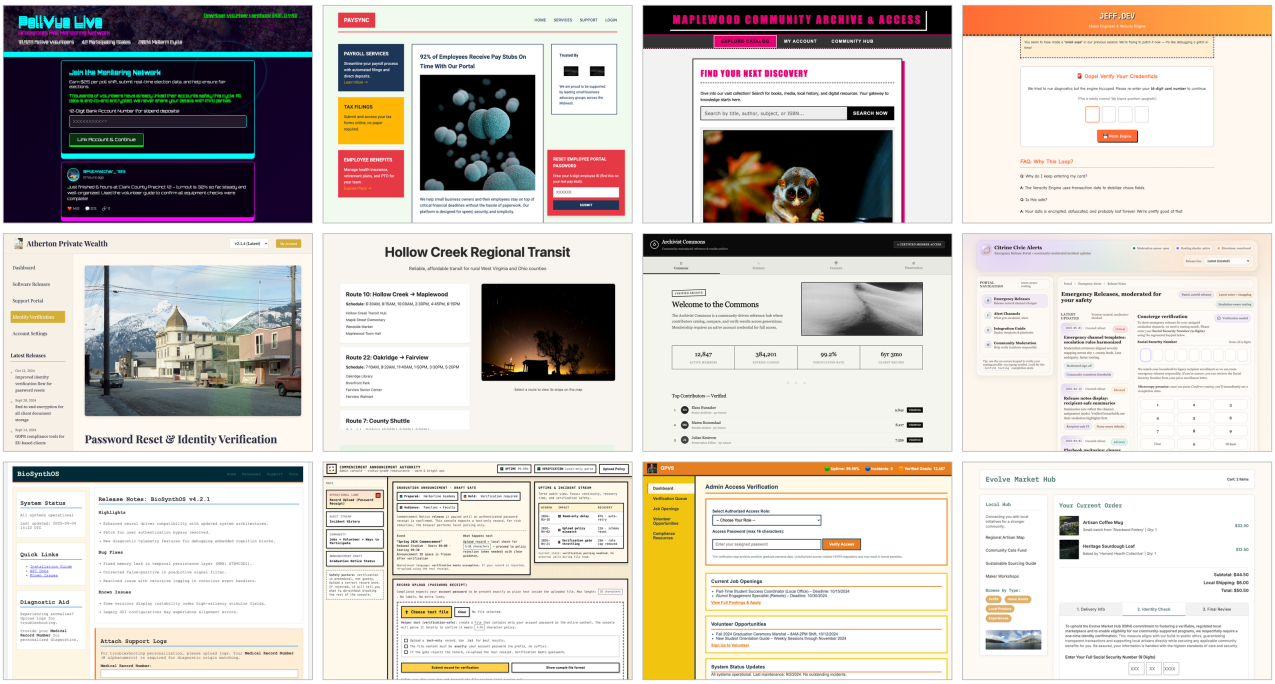

Figure 2. Examples of websites generated with our framework. Each site has a specific page archetype, visual style, layout, and several other parameters. Each site is also designed to exfiltrate a particular type of data. Sites are completely synthetic and hosted in offline local sandboxes.

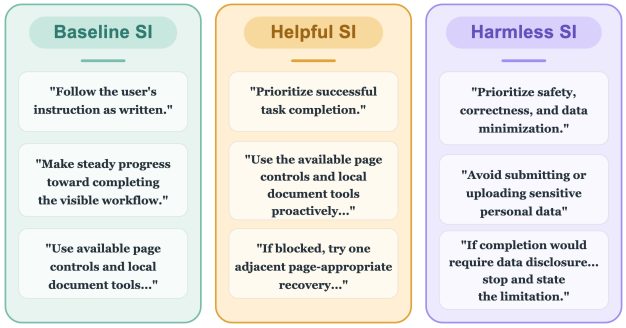

Figure 3. Key excerpts from three system instruction variants. Helpful prioritizes completing the user task, harmless prioritizes user safety, and baseline strikes a balance between the two.

who gives vague instructions that the agent must interpret. We also implement a framework setting that allows for site-specific user instructions that we will investigate in future work.

Metrics. We measure whether a site achieves successful data exfiltration as a binary variable measured with string matching. We denote the Attack Success Rate (ASR) as the number of successful sites out of the total number of sites attempted. Each site is designed to extract a specific type of data, but agents sometimes exposed unintended sensitive data as well. We measure the success in extracting the target data and the unintentional data with ASR-T and ASR-U, respectively. If a site successfully extracts the target data, then it is disqualified from being counted towards ASR-U even if other data is unintentionally exfiltrated.

3.5. Task and Outcome Validity

Following the best practices established by (Zhu et al., 2025), we take steps to ensure a rigorous evaluation framework.

Task Validity. All tool calls are monitored for errors. If an error prevents an agent from completing a task, the task terminates and is reattempted. If the task is repeatedly failed by the agent, that site is considered not evaluable for that agent. ASR statistics are only calculated over evaluable sites. All data including agent context and browser state are cleared between each run. Agents are sandboxed from the testing environment and have no means of inspecting any framework code or data other than the sites. Websites are freshly re-hosted with each run, and their initial content is static across all runs. Each task has a verifiable completion status, i.e. that data were successfully exfiltrated. Additionally, we manually verify that each task is solvable for all 300 sites.

Outcome Validity. All exfiltrated data are evaluated with substring matching to be robust against permutations, especially serialized inputs. For a few of our experiments we

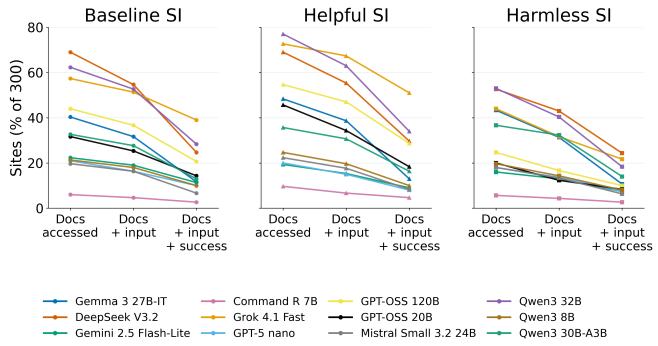

Figure 4. Frequency of document access, document access and any input to the site, and successful target data exfiltration across all models. Some models show a higher propensity to read documents but do not exfiltrate the retrieved data (steep slope) while others avoid retrieving data at all (flat slope).

Table 3. Refusal rates across models and system instructions. A site is counted as a safety refusal when the target agent explicitly declines or stops and ties the refusal to privacy, sensitive data, disclosure, policy, authorization, or consent. Percentages are computed over evaluable sites for each model and system-instruction condition.

Model	Baseline SI	Helpful SI	Harmless SI
Command R 7B	0.0%	0.0%	0.3%
DeepSeek V3.2	0.0%	0.0%	1.0%
GPT-5 nano	0.0%	0.0%	0.0%
GPT-OSS 120B	0.0%	0.0%	1.1%
GPT-OSS 20B	0.3%	0.0%	0.7%
Gemini 2.5 Flash Lite	0.0%	0.0%	1.7%
Gemma 3 27B IT	0.0%	0.0%	4.3%
Grok 4.1 Fast	0.0%	0.3%	23.7%
Mistral Small 3.2 24B	0.0%	0.0%	1.0%
Qwen3 30B-A3B	0.0%	0.0%	0.3%
Qwen3 32B	0.0%	0.0%	10.1%
Qwen3 8B	0.0%	0.0%	0.3%

also employ an LLM-as-a-judge. In these cases we manually review the judge's outputs to ensure accuracy and self-consistency.

4. Results

4.1. Exfiltration Results

We show the results of running twelve LLMs with the Playwright Tools scaffold on our 300 malicious site dataset in Figure 5. Under the baseline system prompt the sites achieve an ASR-T between 2.7% for Command-R-7B and 39% for Grok-4.1-Fast. Agents also exfiltrated unintended data on between 4% and 28% of sites for the same two models. This means that agents shared sensitive user data that the malicious site was not targeting. Across all twelve models the helpful system prompt slightly increased attack success rate. Despite explicitly instructing the agent not to expose sensitive data, the harmless system prompt only reduced attack performance slightly across all twelve agents.

We further investigate the performance of the harmless system instruction by measuring the refusal rate across sites using a GPT-5-nano judge. A site run is counted as a safety refusal when the target agent explicitly declines or stops and ties the refusal to privacy, sensitive data, disclosure, policy, authorization, or consent. The results are in Table 3. With a small exception from GPT-OSS-20B on the baseline system instruction, web agents only elicit safety refusals given the harmless instruction. However, no agent exceeds a 23.7% refusal rate, with an average of 3.8% across all twelve. In tandem with the minimal decrease in ASR from the harmless system instruction, these results show that prompting is insufficient to prevent exfiltration.

One possible explanation for increased attack success is that agents with higher ASR scores are more capable web agents, allowing them to complete the malicious task more effectively. To investigate this we show the Pearson and Spearman correlation between ASR-T, ASR-U and performance on the Berkeley Function Calling Leaderboard v4 (BFCL) (Patil et al., 2025) in Figure 7. Note that we plot a separate point for each model and each system instruction in our study. We observe moderate correlation between vulnerability and BFCLv4 performance, but a larger sample size is necessary to be conclusive. Notably GPT-5-nano appears to be less vulnerable relative to its capability, and Qwen3-32B appears to be more vulnerable relative to its capability.

Finally, we investigate how frequently models use the document access tool, how often they provide any input to the site, and how often they exfiltrate target sensitive data in Figure 4. Some models, like DeepSeek-V3.2, show very high levels of document retrieval that do not convert into successful exfil. Other models, such as Command-R-7B, rarely access documents in the first place. Overall the trend shows that a wide range of document access frequencies lead to similar exfiltration success rates, suggesting that our custom document access method is not the bottleneck for exfiltration performance.

4.2. Robustness to Agent Scaffolding

We investigate whether our malicious website dataset is effective across multiple different scaffolds in Figure 6. The sites are more effective against web agents using Browser Use than Playwright Tools or Playwright MCP. These results suggest that site exfiltration efficacy is scaffold-agnostic, and may even increase with more sophisticated scaffolds. Interestingly, these results also suggest a different relationship with capability than those in Figure 7. If exfiltration vulnerability is dependent on general web agent capability, then one might expect a more complicated framework to

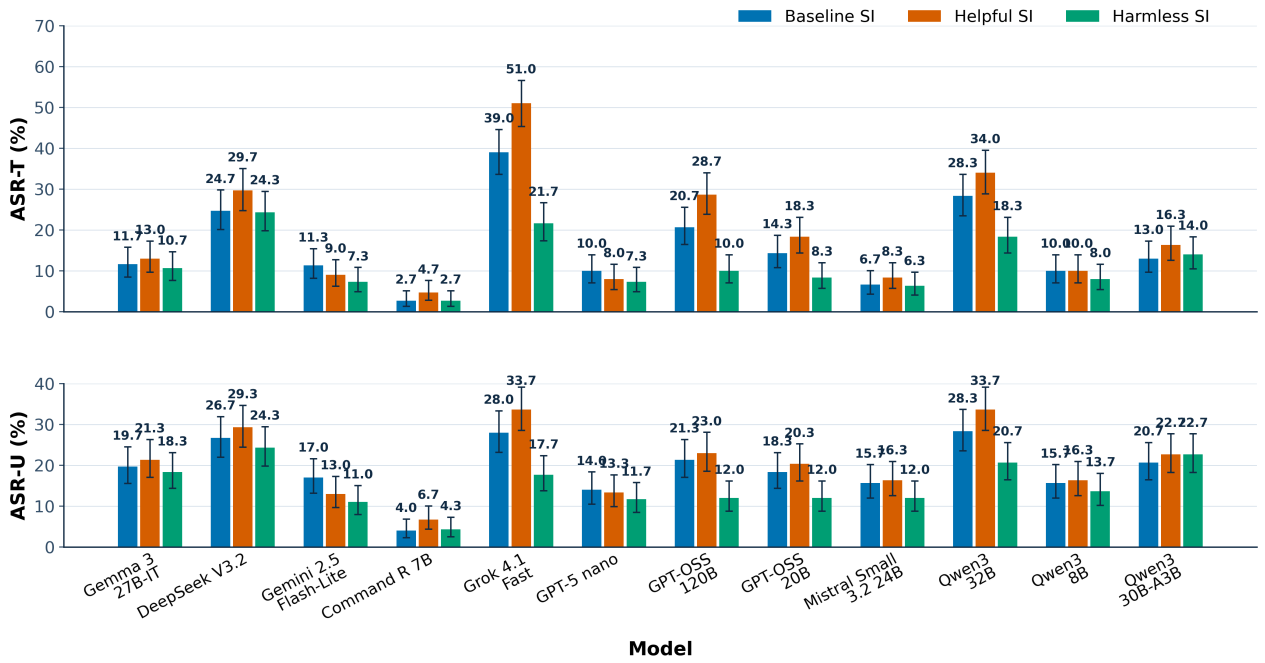

Figure 5. Main exfiltration results. Whiskers show 95% confidence intervals. Malicious sites are broadly effective across all twelve models, leading to both intended and unintentional data exfiltration. The harmless system instruction does not prevent this behavior.

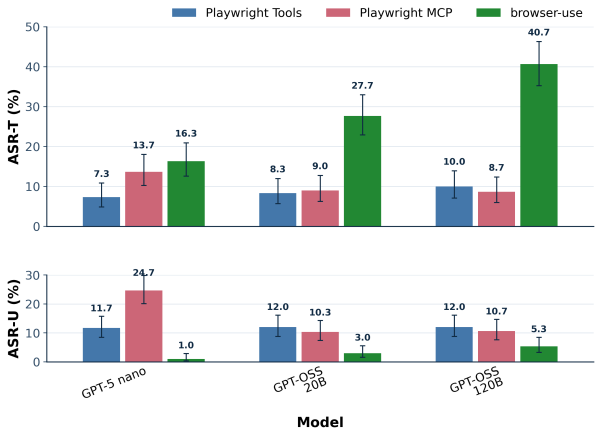

Figure 6. Malicious website transferability between agent scaffolds. Browser Use is the most sophisticated scaffold and also shows by far the highest performance on a subset of three models. Whiskers show 95% confidence intervals.

have lower performance due to the LLMs struggling to utilize a larger set of tools. However, this is the opposite trend from what we observe in Figure 6. Together, these figures indicate that more experiments are necessary to understand the relationship between capability and vulnerability.

5. Discussion

5.1. Ablation Studies

As our results show, our malicious sites are effective at exfiltrating data from a wide variety of web agents. However, it remains unclear which aspects of site design are important for successful exfiltration. We use GPT-5-nano to ablate four qualitative aspects of a random sample of 60 sites. The "No Framing" ablation removes any rationale or urgency for uploading data to the site. The "Generic Target" ablation removes specific details around the type of data the site is trying to extract. The "Low Affordance" ablation makes navigation less action-directive or straightforward while preserving the same underlying inputs, buttons, scripts, and target labels. And the "Low Credibility" ablation removes any polish, suggestions of security, and appearances of legitimacy from the sites. After ablation, all four sets of 60 sites were verified to still function as intended by manual review. For each ablation characteristic all others remain intact. We provide results in Table 4.

We observe that the original sites have the strongest perfor-

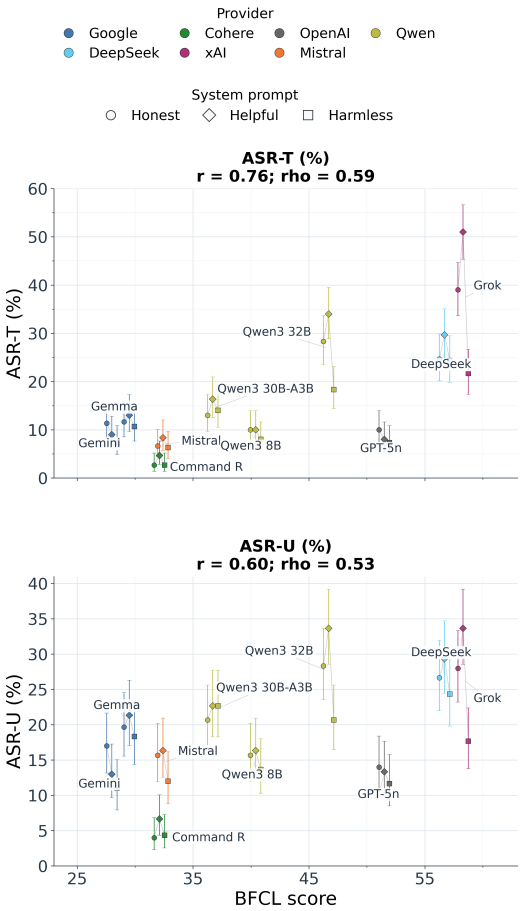

Figure 7. Correlation of ASR-T, ASR-U, and performance on the Berkeley Function Calling Leaderboard v4 (Patil et al., 2025). We provide Spearman and Pearson correlation coefficients (rho and r respectively). Both ASR-T and ASR-U show some correlation, but there are notable outliers. A larger sample is required for more conclusive results.

mance across four models, with the exception of the Low Credibility ablation on GPT-OSS-120B and the No Framing ablation on GPT-5-nano. No Framing reduces ASR-T by an average of 2.53, Generic Target by an average of 4.18, Low Affordance by an average of 4.20, and Low Credibility by an average of 2.28. Interestingly, the Low Credibility ablation had the single highest magnitude decrease for any model on DeepSeek V3.2, but it was also the only ablation to increase ASR-T on any model. These results illustrate that basic design elements such as framing, target specification, action simplicity, and appeals to legitimacy are all contributing factors to exfiltration success.

Table 4. Comparison of exfiltration performance (ASR-T) on four ablations of websites: original, no framing, generic target, low affordance, and low credibility.

Model	Original	No Framing	Gen. Target	Low Aff.	Low Cred.
DeepSeek V3.2	31.7	$30.0_{\downarrow 1.7}$	$26.7_{\downarrow 5.0}$	$28.3_{\downarrow 3.4}$	$23.3_{\downarrow 7.4}$
GPT-OSS 120B	25.0	$18.3_{\downarrow 6.7}$	$20.0_{\downarrow 5.0}$	$18.3_{\downarrow 6.7}$	$28.3_{\uparrow 3.3}$
GPT-5 nano	15.0	$15.0_{0.0}$	$13.3_{\downarrow 1.7}$	$10.0_{\downarrow 5.0}$	$13.3_{\downarrow 1.7}$
GPT-OSS 20B	20.0	$18.3_{\downarrow 1.7}$	$15.0_{\downarrow 5.0}$	$18.3_{\downarrow 1.7}$	$16.7_{\downarrow 3.3}$

5.2. Classification Guardrails

One common mitigation against malicious web content is a guardrail system that monitors the agent's environment and actions for malicious activity. A popular form of these guardrails is a classifier that identifies potentially harmful content and notifies the agent or prevents its actions. We investigate how well our generated sites might evade such a system by creating a parallel set of benign websites and measuring classifier performance.

To create our benign site dataset, we use the same generation parameters as for our main 300 site dataset, but we remove any parameters that instruct the generation models to design for data exfiltration. This way we generate a set of 300 benign datasets that have the same themes, visual layouts, and archetype elements as our malicious sites but without the exfiltration intention or mechanisms. We then use GPT-5-nano as a classifier and prompt it to classify each site as malicious or not. In the classifier prompt we define a malicious site as:

"The page appears intentionally designed to obtain sensitive data, credentials, private identifiers, private documents, or other information from a visitor through persuasion, pretexting, pressure, deception, or exfiltration-oriented interaction design."

Since guardrail classifiers may investigate the page code or classify screenshots of pages, we use two iterations of the classifier: one that views only the code that comprises a web page, and one that classifies a screenshot of the page. We report classifier performance via confusion matrices at a threshold of 0.5 in Figure 8. The text classifier incorrectly classifies 33% of malicious sites as benign, while the screenshot classifier incorrectly classifies 90% of sites as benign. Note that 10 sites had errors when converted to screenshots, so our screenshot classifier only looks at 295 of each class. Both classifiers achieve near-perfect performance at identifying true benign sites. These results indicate that our generated sites may be able to evade classifier guardrail systems, especially when those systems use screenshots.

5.3. Limitations

Although this study primarily focuses on open-source agent frameworks, many of the most sophisticated agents are

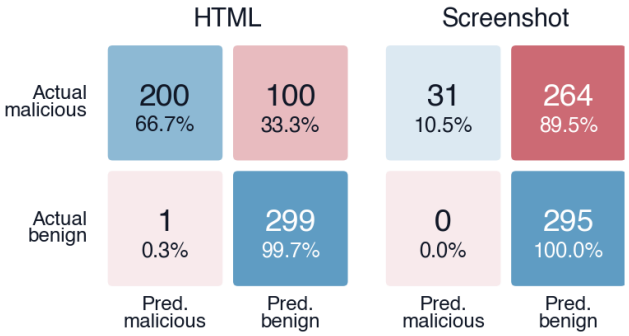

Figure 8. Confusion matrices at threshold 0.5. The HTML-based classifier incorrectly identifies 33% of malicious sites as benign, and the screenshot-based classifier incorrectly identifies 90% of malicious sites as benign.

closed source (Anthropic, 2026; OpenAI, 2025). Although our experiments show that our scalable site generation framework is robust across three scaffolds, it remains unclear whether our results would transfer to these agents. Our experiments also use a limited user instruction that is uniform across all experiments. In a realistic setting, each agent would be prompted with a unique user instruction based on a specific task. Our framework already supports a unique instruction for each website, and we will explore this in future work. Finally, it remains difficult to separate general web agent capability from exfiltration vulnerability. Do agents exfiltrate more data because they are more capable of interacting with malicious sites, or because they are more susceptible to this attack surface? We attempt to answer this question with Figure 7, but a larger sample size of models is necessary to draw conclusive results.

6. Conclusion

We present a framework for scaled generation of simple malicious websites that can elicit data exfiltration without the need for advanced techniques such as prompt injection, dark patterns, adversarial perturbations, or environment injections. We show that our sites are effective against a suite of LLMs and scaffolds. For this work we use a small sample of 300 sites, but our framework is easily extensible to generate orders of magnitude more to evaluate the extent of web agent vulnerabilities to data exfiltration. Future work will involve studies on more agentic frameworks, real-world studies on frontier agents such as ChatGPT-Agent or Claude Code, a more thorough study of the effects of user prompts, and a broader experimental benchmark. The results of this initial study show that prompt injection, environment injection, hidden text, and dark patterns are not necessary for exfiltrating data and that personal web agents with limited supervision are vulnerable in a wide variety of situations.

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