Analysing and strengthening OpenWPM’s reliability

Benjamin Krumnow
TH Köln,
Open University Netherlands

Hugo Jonker
Open University Netherlands,
Radboud University

Stefan Karsch
TH Köln

Abstract

Automated browsers are widely used to study the web at scale. Their premise is that they measure what regular browsers would encounter on the web. In practice, deviations due to detection of automation have been found. To what extent automated browsers can be improved to reduce such deviations has so far not been investigated in detail. In this paper, we investigate this for a specific web automation framework: OpenWPM, a popular research framework specifically designed to study web privacy. We analyse (1) detectability of OpenWPM, (2) prevalence of OpenWPM detection, and (3) integrity of OpenWPM’s data recording.

Our analysis reveals OpenWPM is easily detectable. We measure to what extent fingerprint-based detection is already leveraged against OpenWPM clients on 100,000 sites and observe that it is commonly detected (≈14% of front pages). Moreover, we discover integrated routines in scripts to specifically detect OpenWPM clients. Our investigation of OpenWPM’s data recording integrity identifies novel evasion techniques and previously unknown attacks against OpenWPM’s instrumentation. We investigate and develop mitigations to address the identified issues. In conclusion, we find that reliability of automation frameworks should not be taken for granted. Identifiability of such frameworks should be studied, and mitigations deployed, to improve reliability.

1 Introduction

Web studies rely on browser automation frameworks to accrue data over thousands of sites. The goal of such studies is to provide a view on what regular visitors would encounter on the web. This relies on an (often unstated) assumption that the data as collected is representative of what a regular, human-controlled browser would encounter. Previous works [5, 14, 39, 41] have shown that this is not always the case: websites have been found to omit content (advertisements, video, JavaScript execution, login forms, etc.) or require completion of a CAPTCHA for automated clients. While detectability of automated browsers has been discussed online in various blogs [3, 64, 79] and discussion forums, to the best of our knowledge, so far, no in-depth academic study on the reliability of measurement frameworks built upon such components has been performed.

In this work, we study the OpenWPM framework [27] for measuring web privacy. To date, OpenWPM has been used in at least 76 studies, 60 of which resulted in peer-reviewed publications. As such, its fidelity, that is, the extent to which the web OpenWPM encounters is the web as seen by other web clients, is essential. This point is not lost on its users: several studies explicitly remark bot detection as a possible threat for the validity of their measurements [12, 46, 73]. Recent studies investigated proliferation of generic bot detection [39, 40] and found over 10% of websites employing such techniques. However, it is not clear how these findings translate to OpenWPM. On the one hand, OpenWPM uses a normal browser for collecting data, making it harder to distinguish from other visitors. On the other, OpenWPM targets security and privacy research, an area where malicious actors are to be expected [22, 71]. It is not clear on how many sites OpenWPM could be detected, nor is it clear what effect such detection may have.

In this paper, we address this point. That is, we investigate to what extent OpenWPM provides a reliable record of how websites behave towards any web client. First and foremost, this necessitates understanding how OpenWPM can be distinguished from other clients. Building on that knowledge, we provide a first estimate of how many websites are able to distinguish OpenWPM from human visitors, finding that there are even several websites that can distinguish OpenWPM from other web bots. This allows these sites to use cloaking: responding differently to different clients. Secondly, we investigate whether a website can actively attack OpenWPM’s data collecting functionality. We find several new ways in which a malicious website can attack OpenWPM’s data recording. While both cloaking and data recording attacks are possible,
the question remains whether OpenWPM-detecting sites employ such tactics. Recent work by Cassel et al. [14] finds that Selenium-based bots receive far less third-party traffic, which indicates cloaking happens in practice. We develop a stealth extension for OpenWPM to prevent cloaking and test its performance on sites where OpenWPM-detectors were found.

Contributions. Our main contributions are:

- (Sec. 4) We provide the first analysis of OpenWPM’s detectability based on both conventional fingerprinting [39] and template attacks [63] techniques. We find previously not reported, identifiable properties for every mode of running OpenWPM (headless, Xvfb, etc.), even allowing to distinguish between these modes.
- (Sec. 5) We look for bot detectors in the Tranco Top 100K sites that probe these properties via both static and dynamic analysis. We find a drastic increase of Selenium-based bot detection. In addition, we find detectors in the wild specifically targeting OpenWPM clients.
- (Sec. 6) We explore how sites can attack OpenWPM’s data collection. We find various attack vectors targeting OpenWPM’s most commonly used instruments and implement proof-of-concept attacks for these.
- (Sec. 7) We harden OpenWPM against poisoning attacks and detection. Our hardening hides all identifiable properties when run in native mode and addresses the identified attacks against OpenWPM’s instrumentation. We evaluate its performance against vanilla OpenWPM. The number of cookies received is severely impacted. Conversely, ads/tracker traffic is hardly impacted.

2 Background

OpenWPM. OpenWPM is a valuable tool for web researchers, as it offers increased stability, fidelity and easy access to measurement functionality on top of a browser automation framework (Selenium + WebDriver). The framework can be run under either Ubuntu or macOS. It consists of four parts (cf. Figure 1): a web client, automation components, instrumentation for measurements, and a framework. As a web client, OpenWPM uses an unbranded Firefox browser. In contrast to a regular Firefox browser, this allows running unsigned browser extensions. The various measurement instruments are implemented as browser extensions. They facilitate recording various website aspects, such as JavaScript calls or HTTP traffic. The last part is the framework, which acts as the conductor. Its purpose is to control browsers and data collection. It also adds much-needed functionality, such as monitoring for browser crashes and liveliness, restoring after failures, loading input data, etc.

Use of OpenWPM in previous studies. To understand how OpenWPM is being used, we review the different studies performed to date with OpenWPM. In December 2021, 76 works, of which 57 peer-reviewed, were listed\(^1\) as using OpenWPM. We further add two recent studies that had not yet been listed. For each study, we check the following: what is measured, whether subpages are visited, whether interaction is used, and what run mode is used. Table 1 summarises our findings. Appendix D breaks down our findings for each study individually.

The measures category tallies how many studies used OpenWPM’s various measurement instruments: HTTP traffic, cookies, and JavaScript. Each of these measures may be impacted individually due to bot detection. Interestingly, while most studies use OpenWPM to record HTTP traffic, a few (e.g. [18, 25, 48, 68]) have used it as automation instead as a measurement tool. These are tallied under ‘other’ in Table 1. The other categories pertain to aspects that may impact detectability. In each case, it is currently not known whether these play a role in bot detection. With respect to the interaction category, we note that no study mentioned implementing interaction mechanisms. Therefore, we assume all studies used OpenWPM’s default interaction functionality.

With respect to the run mode category, note that not all studies provide information about this. Nevertheless, the used run mode may impact detectability (e.g. [35]) and thus should be considered. We therefore consider all currently supported modes:

a. Unspecified: study does not specify mode,
b. regular: study uses a full Firefox browsers,
c. headless: study uses Firefox without a GUI,
d. Xvfb: as regular, with visual output redirected to a buffer,
e. Docker: study runs OpenWPM within a Docker container,
f. Virtualisation: study uses virtual machines, possibly in cloud infrastructure.

Lastly, we track whether the studies considered bot detection at all and, if so, whether they used OpenWPM’s built-in anti-detection features. Aside from studies investigating bot

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\(^1\)https://webtap.princeton.edu/software/
3 Related Work

Determining the fingerprint surface of web bots. Browser fingerprinting [24] has been studied extensively in the context of user tracking, as recently summarised in [44]. The idea of using fingerprinting to identify certain client components (such as automation frameworks) has gained more attention recently. Vastel [79] and Shekyan [64] conducted manual investigations of headless browsers to pin down identifiable properties these frameworks. Jonker et al. [39] automated the search for identifiable properties by using a browser fingerprinting library. They compared properties of regular browsers against properties of bots that belong to the same engine class. In contrast, Schwarz et al. [63] applied a new form of fingerprinting (JavaScript template attacks) to perform client-side vulnerability scanning. For a template creation, they traverse object hierarchy and store characteristics of each object. Later on, templates can be compared to determine the difference. Finally, Vastel et al. [80] inspected bot detectors in the wild to collect known identifiable properties. They used these to systematically test the responses by bot detectors to their changes.

Our work comprises the both automated approaches, by Jonker et al. and Schwarz et al., to explore the fingerprint surface of OpenWPM. We apply these systematically to the various run modes of OpenWPM clients, uncovering distinguishers for each mode.

Measuring bot detection in the wild. Two studies exist that carried out a large-scale investigation of the existence of unknown fingerprint-based bot detectors. Jonker et al. [39] scanned 1M websites gathering statically included scripts and analysing these using static code analysis. Shortly after, Jueckstock and Kapravelos [40] presented a similar experiment using dynamic script collection and dynamic analysis. Their presented tool relies on a modified V8 engine to instrument browser functions.

Reliability of scraping results. Recently, multiple studies have been conducted that explore differences between various automated clients, and also between automated clients and human-driven clients in website responses. Ahmad et al. [5] investigate response differences between three classes of bots (HTTP engine tools, headless browsers, and automated native browsers). They found that while HTTP engine tools miss many important resources, they more often pass bot detection than the other two classes. Jueckstock et al. [41] studied differences between headless Chrome and regular Chrome. For regular Chrome, they used a puppeteer-plugin which hides distinguishable properties in Chrome to focus on bot detection. Their results reinforce previous recommendations [27, 79] to not use headless browsers. Zeber et al. [82] contrast data from human users with OpenWPM clients. In their study, OpenWPM clients encountered three times more tracking domains and had more interaction with third-party domains than human-controlled browsers. Cassel et al. [14] investigate the reliability of emulated browsers. To avoid bot detection, they created their own tooling to remotely control a browser. Interestingly, their observations show the opposite of Zeber et al.’s findings. They observed 84% less third party traffic for a Selenium-driven vs. a non-Selenium-driven Firefox browser. This contradiction shows that there is yet no consistent picture for the influence of bot detection on measurements. Further investigation to resolve this conundrum is needed. Any such investigation necessitates tooling that can evade bot detection. We aim to develop such a tool for OpenWPM.

4 Fingerprint surface of OpenWPM

We begin by addressing the research question how can OpenWPM be distinguished from human-controlled web clients? In general, a web site operator looking to identify OpenWPM clients can either probe for identifiable properties (i.e., fingerprinting), or attempt to recognise OpenWPM’s interaction. The latter is due to Selenium, whose interaction was studied in detail by Goßen et al. [34]. Those results fully carry over to OpenWPM. This leaves uncertainty about how OpenWPM’s fingerprint distinguishes it from other clients and other bots. In line with previous works, we call that part of a browser fingerprint that distinguish a certain type of client from other types the fingerprint surface [72]. Determining the fingerprint surface of an OpenWPM client requires a way to find its properties that deviate from properties and values in other clients. Jonker et al. [39] showed that it suffices to consider differences
Table 2: Summary of deviating properties of each OpenWPM setup contrasted with OpenWPM’s Firefox version

| Property                  | macOS | Ubuntu | Docker |
|---------------------------|-------|--------|--------|
| navigator.webdriver is true | ✓     | ✓      | ✓      |
| screen dimension prop.    | ✓     | ✓      | ✓      |
| screen position prop.     | ✓     | ✓      | ✓      |
| font enumeration          | –     | –      | –      |
| timezone is 0             | ✓     | –      | –      |
| navigator.languages prop. | –     | 43     | –      |
| deviating WebGL prop.     | 2037  | –      | 0      |
| Web instrumentation:      | +253  | +253   | +252   |
| - through tampering       | +1    | +1     | +1     |
| - added custom functions  | +1    | +1     | +1     |

Table 3: Screen properties for various configurations

| OS     | Mode       | Resolution | Window X | Window Y | XOffset | YOffset |
|--------|------------|------------|----------|----------|---------|---------|
| macOS  | Regular    | 2560 x 1440| 1366 x 683| 23       | 4       | 0       |
| Ubuntu | Regular    | 2560 x 1440| 1366 x 683| 4        | 4       | 0, 0    |
|        | Headless   | 1366 x 768 | 1366 x 683| 0        | 0       | 8, 8    |
|        | Xvfb       | 1366 x 768 | 1366 x 683| 0        | 0       | 0, 0    |
|        | Docker     | 2560 x 1440| 1366 x 683| 0        | 0       | 0, 0    |

Identification of missing displays. Suppressing output to display (by using Xvfb, headless, or Docker) adds a significant number of differences. In headless mode, the lack of a WebGL implementation leads to thousands of missing properties. We also observe that this mode adds 43 new properties to the navigator.language object. Xvfb mode uses a regular Firefox browser, which contains WebGL functionality. Nevertheless, Xvfb mode causes 5 changed and 13 missing properties. Interestingly, both headless and Xvfb mode allow the detection of missing user elements by accessing the property screen.availTop. This describes the first y-coordinate that does not belong to the user interface. In display-less modes, this is always zero, while regular browsers have larger values.

Traces of virtualisation. Using OpenWPM’s docker container causes the WebGL vendor property to contain the term VMware, Inc. (cf. Table 4) – clear evidence for the use of virtualisation. In addition, the Docker environment reduces the number of available JavaScript fonts to one (Bitstream Vera Sans Mono), nor does it provide information about the time zone.

Table 4: Selected deviations in display-less modes on Ubuntu

| Mode | WebGL vendors | avail[Top|Left] |
|------|---------------|---------|
| RM   | AMD AMD TAHITI| 27,72   |
| HM   | Nul           | 0,0     |
| Xvfb | Mesa/X.org llvmpipe (LLVM 12.0.0,….) | 0,0 |
| Docker | VMware, Inc. llvmpipe (LLVM 10.0.0,….) | 27,72 |

Detecting instrumentation. We checked if using any of OpenWPM’s various instruments has any effect on its fingerprint surface. The only differences occur when using the JavaScript instrument. First, this instrument overwrites certain of the browser’s standard JavaScript objects, which can be detected by using the toString function of a function.
Figure 2: Properties in a (A) original object or (B) by the instrumentation polluted object.

Another identifying aspect of this instrument is the presence of a function in the window object (window.getInstrumentJS), which is not present in any common desktop browser (Firefox, Safari, Chrome, Edge, Opera). Third, OpenWPM’s wrapper functions can be found in stack traces. For that, a script need to provoke an error in any overwritten function and catch the stack trace to successfully identify a modification by OpenWPM. Lastly, the instrument ‘pollutes’ prototypes along the prototype chain of an object. Instrumenting is done by changing the prototype of an object, as well as all its ancestor prototypes. However, the properties of later ancestor prototypes are all added to the first ancestor prototype (cf., Fig. 2). This distinguishes a visitor with instrumentation from one without.

Evaluation. We validate whether the identified fingerprint surface works in practice to identify OpenWPM. For that, we implemented a OpenWPM detector, that uses four tests to identify OpenWPM amongst web clients: (1) test for the presence of a DOM property, (2) test for a missing DOM property, (3) test if a native function was overwritten, (4) compare a DOM property with an expected value.

We tested the detector by setting up four machines, 2 Macintoshes and 2 PCs with Ubuntu. On each machine, we used OpenWPM and common browsers (Chrome, Safari, Opera and Firefox). We tested each distinguishing property from Table 2. Our detector site was able to correctly identify OpenWPM every single time. Almost all properties uniquely identify OpenWPM, except for a few WebGL- and screen-related properties. For a few WebGL properties (roughly 200 of 4K), we found that these also occur on some non-OpenWPM clients. Ignoring all such properties still leaves a large number of identifying properties.

4.2 RQ2: How stable is the fingerprint surface?

We explored how stable our determined fingerprint surface is, as new Firefox and OpenWPM versions may appear frequently. To that end, we repeated our experiments for older version of OpenWPM (0.11.0 and 0.10.0). In general, we found that the fingerprint surfaces largely overlap. For example, on MacOS, the number of WebGL deviations in headless mode increases to 2037 in OpenWPM 0.17.0, from OpenWPM 0.11.0’s 2022. In the oldest OpenWPM version (0.10.0), we find that the JavaScript instrument adds two properties instead of one to the window object (jsInstruments and instrumentFingerprintingApis). In addition, we also investigated whether using an unbranded browser (as OpenWPM does) impacts OpenWPM’s fingerprint. We found no differences between branded and unbranded Firefox versions.

Using outdated browsers, however, does impact the fingerprint. For example, Google’s reCAPTCHA service assigns a higher risk to older browser variants [65]. In the past, OpenWPM’s integrated Firefox version has been behind the official release of Firefox several times (cf. Table 11 in Appendix B). We found that OpenWPM used an outdated Firefox browser 71% of the last 20 months. In short, this distinction vector should be expected when using OpenWPM.

5 Incidence of OpenWPM detection

To assess the extent of OpenWPM detection in the wild, we conduct a large-scale measurement for client-side bot detection. In detail, we focus on scripts with capabilities to detect OpenWPM, i.e. scripts with routines to access properties unique for Selenium-based bots and/or OpenWPM. We find both general Selenium detectors and OpenWPM-specific detectors.

5.1 Data acquisition and classification

Methodology. Previous automated approaches [39, 40] to identify bot detectors have either relied on static or dynamic analysis. The idea behind static analysis is to identify code patterns in source code that link to known bot detectors or that use specific bot-related properties. A limitation is that scripts may create code dynamically, which will be missed
out by static analysis. Moreover, minification and obfuscation further increase the false negative rate of static analysis. The alternative approach, dynamic analysis, is to monitor JavaScript calls that identify a script as a bot detector based on access to bot-related properties. Dynamic analysis does cover dynamically-generated scripts. Moreover, it does not monitor the code itself, but only executed calls. An upside of this is that neither minification nor obfuscation affects the analysis. On the other hand, code that happens not to be executed during the run, is not analysed. Both static and dynamic analysis have been able to identify some bot detectors in the wild. It is not clear whether and to what extent the results of the methods differ in practice for finding web bot detectors. We combine both methods to increase coverage.

Setup. In order to assess the extent of client-side bot detection, we scan the top 100K websites of the Tranco list [45]. We set up an instance of OpenWPM running Firefox in regular mode. During a site visit, our OpenWPM client stores a copy of any transmitted JavaScript file and records JavaScript calls. We add an initial waiting time of 45 seconds after a completed page load to give websites enough time to perform JavaScript operations. In addition, we instruct our client measures the presence of bot detection on subpages by opening a maximum of three URLs extracted from a site’s landing page. For selecting subpages, we consider only URLs linking to the same domain. Within this and the following sections, we apply scheme eTLD+1 to identify a domain. To account for websites that use same origin requests to redirecting clients to foreign domains, our client checks if a foreign domain was entered after following all redirects.

Scripts should be classified as bot detectors if they access the fingerprint surface of OpenWPM. However, certain scripts may access these attributes for other purposes, such as checking supported WebGL functionality. To reduce such false positives, we only classify a script as bot-detecting when it accesses properties pertaining to browser automation or are unique to OpenWPM (cf. Sec. 4.1). This leaves only the following: navigator.webdriver, which is specific to WebDriver-controlled bots; and the new identifying properties introduced by OpenWPM’s JavaScript instrumentation: getInstrumentJS, instrumentFingerprintingApis, and jsInstruments. Table 5 shows the results of the data collection and classification.

Limitations. Inherent in the above approach are several assumptions that can impact the results. First, our approach relies on the fingerprint surface we established. Detectors based on other methods (e.g., mouse tracking [16]) will be missed. Second, we do not account for cross-site tracking. A third-party tracker could classify our client as a bot on one site and would need only to re-identify the client on another site, e.g., using IP filtering or regular browser fingerprinting. This amounts to a form of website cloaking – serving different content to specific clients. To what extent third party tracking in general employs cloaking is a different study and left to future work. Both these limitations may cause underestimation of the number of detectors (false negatives). As such, our approach approximates a lower bound on the number of detectors in the wild.

Preprocessing for static analysis. Within the static analysis, we pre-process scripts to undo straightforward obfuscation. We derive the respective encoding, transform hex literals to ASCII characters, and remove code comments. We apply our static analysis to scripts that we collected during our scan of the Tranco Top 100K, which resulted in 1,535,306 unique scripts. To identify Selenium-detector scripts, we then use patterns to look for access to navigator.webdriver (more details can be found in Appendix C).

Using honey properties to catch iterators. For the dynamic analysis, every recorded access to the fingerprint surface identifies a script with the potential to detect OpenWPM as a bot. This will also be triggered by scripts that iterate over all properties, e.g., for regular browser fingerprinting (re-identification). Determining the purpose of such iteration requires per-script manual inspection and goes beyond dynamic analysis.

To determine whether property iteration takes place, we extend our client’s navigator and window object with ‘honey’ properties. These honey properties are added on the fly and use random strings as name. Hence, only a script using property iteration would access all honey properties. We assign scripts that use property iteration into three categories, based on access to the navigator.webdriver property: definitely detecting bots, and inconclusive. Iterator scripts are classified as inconclusive if they do not access navigator.webdriver, as all accesses to the fingerprint surface could be due to property iteration. Scripts that iterate the navigator object will naturally access the webdriver property. To check whether this access is only by iteration or intentional, we distinguish between scripts that trigger our static analysis and those that do not. Only scripts that do not surface in the static analysis are classified as inconclusive.

5.2 RQ3: How often is OpenWPM detected?

Our results show that, when checking both front- and sub-pages, at least 16.7% of websites in the Tranco Top 100K execute scripts that accessed properties specific to Selenium and, thereby, OpenWPM. Moreover, we also find scripts accessing OpenWPM-specific properties.
### Table 5: Number of websites with Selenium detectors

| # sites | static | dynamic | union |
|---------|--------|---------|-------|
| identified | 32,694 | 19,139 | 38,264 |
| without false positives / ‘inconclusive’ | 15,838 | 16,762 | 18,714 |

### Table 6: Number of sites ordered by script domains accessing OpenWPM-specific properties

| | cz | gs | google.com | ad1t |
|---|---|---|---|---|
| total | 331 | 14 | 9 | 2 |
| jsInstruments | 331 | 5 | 2 | 2 |
| instrumentFingerprintingApis | 0 | 6 | 4 | 0 |
| getInstrumentJS | 0 | 3 | 3 | 0 |

*cz: cheqzone.com, gs: googlesyndication.com, ad1t: adzouk1tag.com*

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**OpenWPM-specific properties are accessed in the wild.**

Most scripts we found recognise OpenWPM by targeting Selenium. A small number of detectors, also include specific routines to detect OpenWPM itself. Overall, 356 sites executed scripts that accessed OpenWPM-specific properties. These scripts were all included via third-party domains, belonging to four distinct providers. Table 6 summarises these detectors and their detection method. Detectors on cheqzone.com were found by both static and dynamic analysis; detectors on the other three domains used some form of minification, obfuscation, and/or dynamic loading, and were only found by dynamic analysis. We investigated the four hosting domains by consulting whois records, EasyList, and the WhoTracksMe database [17]. All domains are related to the advertising industry. The domain cheqzone.com belongs to CHEQ, a company fighting ad fraud. The scripts hosted by Google domains are included through Google’s reCAPTCHA service. While we could not clarify the origin of adzouk1tag.com, we found this domain listed in the EasyList for ad domains.

**14% of sites have bot detection on the front page.** Figure 4 depicts the distribution for detectors active on the front page of websites for static and dynamic analysis. Dynamic analysis without considering property iteration identifies 12,208 sites with detectors on the front page. Static analysis measures the number of sites where bot detection could be triggered (11,897), including those where detection is present but not (yet) executed, e.g., where detection is only triggered after hovering over certain elements. While both static and dynamic analysis identify a similar number of detectors for each bucket, they do not fully overlap. Combining both provides a slight increase in the presence of detectors (~1.7K sites).

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**Deep scanning increases the rate of detection by 5 per cent points.** As discussed in Section 2, 15% of studies conducted with OpenWPM (also) investigated subpages. This raises the question whether such studies are more often subject to bot detection, that is: does bot detection occur more frequently on subpages? Figure 3 depicts the occurrence of bot detectors on front pages and subpages. In general, studies examining subpages are at greater risk to be detected: the number of sites with active detectors increases for by at least 37%. Hence, the average detection rate within the Top 100K sites will increase. That is: the study will be exposed to more detectors. Combining the results of both measurements, we see an increase of 5 per cent points (from 14% to 19%).

### 5.3 RQ4: By whom is OpenWPM detected?

To explore this question, we separated detectors into first and third parties. We find that the majority of sites includes detectors from third-party domains. We count how often scripts on these third-party domains are included on scanned sites, tallying each third-party domain once per including site. Some sites include more than one detector, hence the total number of inclusions exceeds the number of sites with detectors. Overall, we count 3,867 first-party detector scripts and 21,325 third-party detector scripts.

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1. https://easylist.to/easylist/easylist.txt
First and third-party bot detection are used differently among the industry. We further explore what sites include detectors, as this may provide a better view on what bot detection is used for. For that, we collect categories for the identified 16K websites with detectors based on Symantec’s site review service (https://sitereview.norton.com/). Sites may be assigned multiple categories; for such sites, we tally each listed category. Figure 5 depicts the 16 most often tallied categories for both first-party detectors (4,198 times) and third-party detectors (16,323 times). We find that news sites are responsible for 18.4% of all third-party inclusions, followed by Technology (9%) and Business (7%). Interestingly, the ranks for Shopping (16.4%) and News (5%) switch for first-party detector inclusions. Moreover, sites in the categories Finance (8% vs 3%) and Travel (7% vs 2%) make up for a larger portion in the set of first-party inclusions than for third parties.

We believe that these uneven distribution of inclusions is explainable. While every site owner will want to protect their site from nefarious bots (and thus reason to include first-party detection), advertising has become a popular business model for websites. For such sites, third parties have a vested interest in detecting bots: to detect ad fraud. Thus, on such sites, one would expect more third-party bot detection.

Third-party bot detection typically serves the advertisement industry. Following up on the previous point, we investigated the origins of third-party detectors. Table 7 breaks down the most common included domains. The top 10 domains account for two third of inclusions. The site WhoTracks.me [17] categorises trackers according to purpose. Using this, we find that the bot-detecting scripts on the most commonly included domains can serve a variety of purposes. For example, yandex.ru offers scripts used for advertising, content delivery network, site analytics, social media, and others. Other uses include web analytics (crazyegg.com), CDN (jsdelivr.net) and live chat (intercomcdn.com). However, bot detection is most commonly deployed by advertisers (e.g., domains 2,3,4,7,9, and 10 in Table 7).

The vast majority of first-party detectors are embedded third parties. To determine the origins of first-party bot detection scripts, we look for similarities between their inclusions of detectors. To do so, we hash the scripts and check for structural similarities in script URLs (for more details see Appendix A). We found various similarities amongst unrelated sites. Scripts originating from Akamai occur the most frequent (1,004 sites). Second is Incapsula (998 sites), third is an unknown bot detector (659 sites), and fourth is Cloudflare (486 sites). Together, these top three originators account for 3,147 out of 3,867 sites (88%) where we found first-party detectors. In contrast to the purpose of third-party detectors, first-party detectors are not supplied by advertisement companies. Moreover, Akamai, Incapsula and Cloudflare all offer commercial bot detection services. With that in mind, one should expect sites with first-party detectors to likely tailor their responses for detected bots (e.g., throttling, blocking, withholding resources, and serving CAPTCHAs).

### Table 7: Domains hosting 3rd-party detector scripts

| Hosting Domain       | # Inclusions (1/site) |
|----------------------|-----------------------|
| all                  | 21,325  100%          |
| 1 yandex.ru          | 3,848   18.04%         |
| 2 adsafeprotected.com | 2,309   10.83%         |
| 3 moatads.com        | 2,165   10.15%         |
| 4 webgains.io        | 2,091   9.81%          |
| 5 crazyegg.com       | 1,552   7.28%          |
| 6 intercomcdn.com     | 1,061   4.98%          |
| 7 teads.tv           | 854     4.00%           |
| 8 jsdelivr.net       | 423     1.98%           |
| 9 mxcdn.net          | 416     1.95%           |
| 10 mgid.com          | 402     1.89%           |
| 11+ remaining 704 domains | 6,204  29.1% |

6 Attacking JavaScript recording

We investigate whether a malicious website or third party could corrupt OpenWPM’s data collection process. In particular, we consider an attacker that can deliver arbitrary content (HTML, cookies, JavaScript), but cannot break the browser’s security model. To do so, our focus resides on attacks against the integrity or completeness of measurements. More specifically, we aim to attack the resilience of OpenWPM’s most commonly used instruments: HTTP traffic, cookie recording, and JavaScript call recording. Both HTTP and cookie instruments are simple wrappers around browser functionality. Breaking them thus requires breaking the browser, which is outside the attacker model. The JavaScript instrument, on the other hand, needs to supply all its monitoring functionality itself. It is therefore clearly in scope of our attacker model.

Since the instruments focus on data recording, we investigate attacks on data recording. More specifically, we consider:
We found a vulnerability that, when successfully exploited, allows a website to break OpenWPM’s data recording hooks. The vulnerability can be leveraged to turn off recording of JavaScript calls in the JavaScript instrument.

Instruments in OpenWPM are implemented as a browser extension. Extensions are isolated to protect higher privilege APIs from access by untrusted code. Website scripts thus cannot directly interact with extensions. However, both extensions and website scripts can read and change the DOM, opening the door for injection attacks against extensions that read the DOM. We conducted source code analysis for each instrument under investigation to identify vulnerabilities to such attacks. Below we discuss the found vulnerabilities.

6.1 RQ5: How to prevent data recording?

We found a vulnerability that, when successfully exploited, allows a website to break OpenWPM’s data recording hooks. The vulnerability can be leveraged to turn off recording of JavaScript calls in the JavaScript instrument.

More specifically: the JavaScript instrument overwrites several API functions by hooking into the DOM’s event dispatcher (to record access to them). The event dispatcher then sends messages to be recorded back to the JavaScript instrument’s back end. To prevent an attacker from silently undoing these hooks, OpenWPM also hooks into (and thus: records access to) setters and getters to these API functions themselves. However, the event dispatcher itself is not protected. We thus can alter the event dispatcher to inject our own messages and manipulate messages sent to OpenWPM (cf., Listing 2). To carry out this attack, the attacker overrides the event dispatcher to block all messages (all events from instrumented objects). This would already block OpenWPM recording, by breaking any JavaScript API calls. However, this also would break a website’s own JavaScript. To block only OpenWPM messages, the block needs to be tailored. Conveniently, tags messages with an ID to identify any monitored objects. Though this ID is randomly generated, it can easily be determined: simply trigger an API call to a monitored object, acquire the random ID from the observed message, and update the event dispatcher to only block messages containing this ID.

6.2 RQ6: Can fake data be injected?

The previous attack, altering the event dispatcher, not only allows an attacker to block data recording, it also allows an attacker to learn the ID OpenWPM uses to record data. This is sufficient to inject almost arbitrary messages to be recorded. The attacker simply creates a custom event following the format used by OpenWPM’s JavaScript extension and includes OpenWPM’s assigned event ID. This enables an attacker to define most of the content of the resulting entry in OpenWPM’s recording, such as the executing script URL or which function was called. Crucially, though, the website that originated the call is set outside of the browser by OpenWPM. The data sent by the event dispatcher is properly sanitized by the back-end, which prevents spoofing this. We can thus only inject fake data for the currently visited website. Note that a third party included on the site can also execute this attack.

6.3 RQ7: Can records be deleted or altered?

Whereas the previous attacks exploited a vulnerability in the DOM-parsing front-end of the respective instruments, deleting already recorded data requires manipulating an instrument’s back-end, for OpenWPM: SQLite. Attacking a database back-end requires an SQL injection vulnerability. As already mentioned, OpenWPM’s data recording back-end properly sanitizes its inputs. This means that there is no possibility for an SQL injection via JavaScript recording. Therefore, we conclude that it is not feasible to delete or alter already recorded data from OpenWPM’s SQLite database.

6.4 RQ8: Is data recording complete?

We investigated whether data recording is complete. We found two different attacks against completeness: existence of unobserved channels, and silent delivery of JavaScript code.

Existence of unobserved channels: During our evaluation, we found a way to bypass OpenWPM’s recording of JavaScript function calls. This attack again exploits OpenWPM’s hooks to record function calls. In particular, the hooks must be attached to every object that is to be observed. For every new window or iframe, this must be done afresh. However, there is a long-standing bug in Chrome and Firefox (cf., [67]), where both browsers under some circumstances fail to inject scripts into iframes. We tested if OpenWPM’s implementation is affect by this and we found that this is indeed the case.

```
Listing 2: Turn off the script recorder

//Step I: Retrieve OpenWPM’s random ID
function grabID() { return new Promise((resolve, reject) => {
  let id;
  document.dispatchEvent = function (event) {
    id = event.type; document.dispatchEvent = dispatch_fn;
    if (id !== undefined) { resolve(id); }
    else { reject(new Error(msg)); }
  }
  // Perform an action to grab the ID
  navigator.userAgent;}
  // Step II: Overwrite event dispatcher to block events
  async function attackExtension() {
    let id = await grabID();
    document.dispatchEvent = (event) => {
      if (event.type !== id) { dispatch_fn(event); // Dispatch event
        else { console.log('Event swallowed: *+event');]}}
    }
  }
  attackExtension()
```
Our evaluation of this attack involves two different ways to access an iframe’s DOM\(^6\) to create/execute iframes and their code: static vs. dynamic creation and immediate vs. delayed execution. Of these, immediate code execution (at creation time) is required to successfully exploit this bug. None of the other parameters we tested influenced the result. Listing 3 shows a proof-of-concept of this type of attack.

**Silent delivery of JavaScript code:** Note that the aforementioned attacks based on JavaScript would appear in OpenWPM recordings, if the HTTP instrument is used. Namely, that instrument collects response bodies. That is, unless this instrument’s recording can also be bypassed. We indeed managed to extend our previous attacks to be silently transferred to OpenWPM. For that, we looked at the two options that OpenWPM offers two to collect response bodies. OpenWPM either stores all response bodies (full coverage), or it can be set to store JavaScript files only. The latter option significantly reduces stored content. For this mode, we found that an attacker can silently deliver JavaScript code by sending it as text and processing it client-side, e.g., by including a line like `<link src="server.com/payload" content-type="text/plain">` in the HTML source. To successfully bypass OpenWPM’s traffic recording of JS files, three aspects must be accounted for:

i. The content-type attribute must be set to something other than text/javascript;

ii. The src attribute must not contain a “.js” extension;

iii. the delivered file is not automatically executed; this must be handled by a different client-side script (e.g., using `eval()`).

```javascript
// Operation will not appear in the recordings.
setTimeout(() => {
    let element = document.querySelector("#unobserved");
    let iframe = document.createElement('iframe');
    iframe.src = "unobserved-iframe.html";
    element.appendChild(iframe);
    iframe.contentWindow.navigator.userAgent;
    iframe.contentWindow.navigator.userAgent;
}, 500);
```

Listing 3: Example of an unobserved channel

7 Improving OpenWPM’s reliability

This section focuses on OpenWPM’s reliability as an instrument measuring the web as encountered by regular visitors. We explore how and to what extent reliability can be improved. To do so, we design an approach to hardening OpenWPM’s instrumentation and to hiding its distinctive fingerprint (from here on referred to as \(WPM_{\text{hide}}\)). Our proof-of-concept successfully hides the telltale signs of OpenWPM from its fingerprint and makes OpenWPM robust in the face of the discussed attacks in a lab setting. To evaluate its effectiveness in an open world setting, we run \(WPM_{\text{hide}}\) against detectors in the wild and contrast its measurements with those of a regular OpenWPM client.

7.1 RQ9: How to hide the fingerprint surface?

OpenWPM’s characteristic fingerprint varies with the various modes of running OpenWPM. For example, in headless Firefox mode, the fingerprint surface is difficult to hide due to headless mode’s lack of functionality when compared to regular browsers. Hence, we focus on run modes where OpenWPM runs the browsers natively (Regular Mode). For such modes, we achieve stealth by overriding properties without leaving traces. These techniques can also be applied in other run modes (e.g., virtualisation).

The identifying properties for Regular Mode (see Table 2) relate to the webdriver property, window position, and dimension. Of OpenWPM’s various instruments, only the JavaScript instrument causes further identifiable properties. Hiding these properties can be achieved by a customized browser, or by including additional code inside a page’s scope. Implementing the former requires significant work, but it can hide the fingerprint near-perfectly. The latter approach is far simpler to implement but risks leaving residual traces. For our proof-of-concept, we choose the second option, as it can be seamlessly integrated within the current OpenWPM framework without significant effort.

Our proof-of-concept must address two aspects: hiding the automation components and preventing detection of instrumentation. To prevent detection of instrumentation, four issues need fixing (Sec. 4.1): (1) calling the `toString` operation of overwritten functions must return the regular output string for browser functions; (2) no additional property may appear in the DOM; (3) stack traces must not show any signs of the instrumentation; (4) prototype pollution must be avoided. Lastly, hiding instrumentation requires hiding their detectable aspects, similar to how `toString` must appear unchanged.

**Preserve `toString` output.** For the first issue, we found that CanvasBlocker\(^7\) addresses this well. Its implementation successfully fools all our fingerprinting tests (Sec. 4). CanvasBlocker creates a getter function with an identical signature to the function that must be overwritten and attaches it to the DOM based on a specific Firefox feature called `exportFunction`. The newly exported function is then used to redefine the getter of a object’s prototype for a specific property. As a result, the overwritten function returns the native code string like a default browser property (cf., Listing 1).

\(6\)window.frames[0], and frame.contentWindow

\(7\)https://github.com/kkapsner/CanvasBlocker
Normally, accessing the getter of an object’s prototype leads to an error. If this getter is replaced with a custom getter, that error is never thrown. This makes tampering with properties via an object’s prototype detectable [34]. Calling the original getter from the customised getter results in the original error being thrown, addressing this aspect of the fingerprint surface.

**Preserve clean DOM.** The second issue arises during page load, prior to the page’s JavaScript activation. The instrumentation injects its code as script from the content context into the page context, overwrites the needed properties, and removes its code from the page context again. However, in practice, not all injected functions are deleted. We update the instrument to overwrite all functionality directly from the content context, thus keeping the page context clean.

**Faking stack traces.** The third issue requires the stack trace to show no signs of instrumented functions. A web page can only access stack traces if errors occur. Normally, if an error occurs, the stack trace would show that the called function is called from inside the instrumentation. We address this by catching each error and throwing a new error with properly adjusted values for file name, column, message, and line number.

**Avoid prototype pollution.** The last issue relates to the pollution of an object’s prototype, as OpenWPM’s instrument modifies only the first prototype in the prototype chain. We address this by overwriting properties per prototype. Unfortunately, this approach has its own limitation, as it is not possible to determine the caller of a function, when a prototype has multiple children. Especially for prototypes located higher up the chain, the number of children increases; raising the potential to capture unwanted API calls on other children objects. To test our implementation, we instrumented the same API calls as used by OpenWPM. Luckily, most of our these APIs are provided by prototypes close to the bottom, which allows us to cover a wide set of OpenWPM’s instrumented APIs.

**Preventing detection of automation components.** The automation components are detectable by window size, window position and the webdriver attribute. For the latter, our hidden version must set the `navigator.webdriver` property to false like a regular Firefox browser. Since Firefox version 88, this flag is not user-settable.\(^8\) We override the getter function of the `navigator.webdriver` property in the same fashion as described in the previous section. To change OpenWPM default window settings, we introduce a settings file that makes the window size and position settable in OpenWPM.

\(^8\)https://bugzilla.mozilla.org/show_bug.cgi?id=1632821

### 7.2 RQ10: How to mitigate recording attacks?

**Securing messaging from page context to background context (see Sec. 6.4).** To address the tested variants of incomplete recordings, we use CanvasBlocker’s frame protection. The basic idea is to intercept APIs used by page scripts to modify the DOM or create a new, non-instrumented copy of the DOM. This ensures that each modification or newly constructed DOM contains the instrumentation. Our implementation covers five cases: window constructors, DOM modification API, window mutations, and DOM creation via the `document.write` API, and finally the `window.open` API.

**Filtering of the HTTP file recorder (see Sec. 6.4).** To the best of our knowledge, there is no known way to distinguish JavaScript code from text that is robust against a dedicated obfuscator. Therefore, an active adversary should be assumed to be capable of hiding JavaScript in a way that would accidentally be filtered out. Since this issue only arises in the presence of active adversaries, we recommend in such a case not to use any filtering.

### 7.3 Evaluation of PoC implementation

We developed a proof-of-concept implementation to hide the tell-tale signs of automation and to mitigate the found attacks. We evaluate the impact of our proof-of-concept implementation (from here on, WPM\(_{hide}\)) on web measurements when encountering bot detection in the wild. To that end, we contrast its results with vanilla OpenWPM (from here on: WPM) in HTTP traffic, cookies, JavaScript execution, and delivered JavaScript files. We test on all sites with bot detectors (as found by dynamic analysis) from the Tranco Top 5K (see Sec. 5). This list contains 1,417 sites with either first-party or third-party detectors. On these sites, we run WPM and WPM\(_{hide}\) in parallel (OpenWPM v.0.18.0, regular mode,
HTTP, JavaScript and cookie instrument activated) and configure each browser to idle 60 seconds on a page after loading completed. We take steps to mitigate noise in measurements. In particular, we avoid cross-client interferences by separating both crawlers via two individual machines and IP addresses. Each IP address belongs to a residential network and comes from the same municipal and internet provider, which avoids differences caused to cloud-based IP blocking [37] and geo-location. Secondly, we re-synchronise the machines every 100 visit. This ensures that sites are loaded roughly simultaneously on both machines (max. offset is below four minutes).

**Sites that detect OpenWPM serve less media resources.**
In our experiment, we found that WPM\(_{\text{hide}}\) encounters 3.45% more HTTP requests. As our data set is not normally distributed, we tested for significance using Wilcoxon signed-rank test with a confidence interval of 95%. For that, we divided the traffic into first and third-party requests and find significant differences for HTTP requests to both first- and third-parties (\(p\)-value < 0.0001). In more detail, we found for WPM, 175 sites (12%) lead to more first-party and 472 sites (33%) to more third-party requests. For WPM\(_{\text{hide}}\), we count 400 sites (28%) with more first-party and 654 sites (46%) with more third-party requests. This indicates a stronger variability in third-party traffic, leaning towards less detectable clients.

Table 8 shows requests for each machine per requested resource type.\(^9\) The table shows that WPM\(_{\text{hide}}\) receives roughly double the number of audio and video files (type media). Moreover, requested images (image and imageset) is increased by \(\sim\)3%, and executable code (script) by \(\sim\)4%. Moreover, WPM incurs three times the number of CSP violations – though this may also be due to embedding more JavaScript in the page context. Finally, the difference in websocket requests is due to a single outlier. Thus, we do not expect websocket requests to change significantly between WPM and WPM\(_{\text{hide}}\).

**Equivalent amount of ads/trackers traffic.** To assess the amount of trackers and advertisers in traffic, we use the same approach as previous works \([5, 14, 41]\): use the EasyList and EasyPrivacy blocklists\(^10\) to identify trackers. Our results show that WPM and WPM\(_{\text{hide}}\) encounter a near equal rate of advertisers and trackers. For WPM, ads and trackers account for 14.3% and 11.6% of total traffic. For WPM\(_{\text{hide}}\), this is 14.2% and 11.5%, respectively – almost equivalent.

**Large differences in served cookies.** For cookies, we contrasted the number of cookies between both variants. We found that these differ significantly for both first parties and third parties (\(p\)-value < 0.0001). Specifically, 305 sites serve WPM\(_{\text{hide}}\) more first-party cookies, while only 146 sites serve WPM more first-party cookies. Interestingly, the opposite is true for third-parties. Here we find 824 sites whose third parties offer WPM more cookies than WPM\(_{\text{hide}}\); the other way around happens for the third parties of 227 sites. In total, the number of cookies is 55,853 (WPM) vs. 46,736 (WPM\(_{\text{hide}}\)). Using WPM\(_{\text{hide}}\) thus leads to a decrease of 16.32% of cookies.

We also looked at cookies as possible means to track users. To determine whether a cookie can be used for web tracking, we use the approach of Englehardt et al. \([28]\), as refined by Chen et al. \([15]\). According to this method, a cookie may be used for tracking when: (1) it cannot be a session cookie, (2) the length of the cookie is 8 or more characters (excluding surrounding quotes), (3) the cookie is always set, and (4) the values differ significantly based on the Ratcliff-Obershelp algorithm \([10]\). While 5,307 cookies satisfy these criteria for WPM, only 2,282 cookies for WPM\(_{\text{hide}}\) match; a decrease of 57%.

### Table 8: Comparison of HTTP request resource types

| Resource type | WPM | WPM\(_{\text{hide}}\) | Diff. |
|--------------|-----|---------------------|------|
| csp_report   | 884 | 298                 | -66.29% |
| websocket    | 467 | 242                 | -48.18% |
| media        | 378 | 552                 | +46.03% |
| beacon       | 3,804 | 4,453            | +17.06% |
| imageset     | 4,888 | 5,432            | +11.13% |
| xmlhttprequest | 46,199 | 49,398         | +6.92% |
| script       | 73,527 | 76,430           | +3.95% |
| object       | 53  | 55                  | +3.77% |
| other        | 92  | 95                  | +3.26% |
| main_frame   | 3,883 | 3,757             | -3.24% |
| image        | 101,256 | 103,801         | +2.51% |
| sub_frame    | 11,119 | 10,885           | -2.10% |
| stylesheet   | 9,663 | 9,840              | +1.83% |
| font         | 9,557 | 9,704              | +1.54% |
| **Total**    | 265,770 | 274,942         | +3.45% |

WPM\(_{\text{hide}}\) encounters roughly 3 times the number of CSP violations – the other way around happens for the third parties of 227 sites. In total, the number of cookies is 55,853 (WPM) vs. 46,736 (WPM\(_{\text{hide}}\)). Using WPM\(_{\text{hide}}\) thus leads to a decrease of 16.32% of cookies.

8 Conclusions

**Reliability of automated measurements on trial.** Our work demonstrates that OpenWPM is susceptible to attacks threatening its reliability. In particular: virtualisation makes scaling web studies easy, but turned out to undermine OpenWPM’s reliability as a measurement tool. It is an open question whether other automation / measurement frameworks suffer similarly from virtualisation.

**Bot detection on the rise.** In comparison with previous studies, we see the number of sites looking for the webdriver property has significantly increased in the span of less than one year (Tbl. 9). This rapid change clearly suggests that web sites are swiftly transitioning to responding differently to automated clients than to regular clients. Web studies should

\(^9\)https://developer.mozilla.org/en-US/docs/Mozilla/Add-ons/WebExtensions/API/webRequest/ ResourceType

\(^10\)https://easylist.to/
Table 9: Studies measuring webdriver property access on front pages

| when   | analysis       | corpus      | # sites | %    |
|--------|----------------|-------------|---------|------|
| [40]   | 2019–10        | dynamic     | Alexa 50K | 2,756 | 5.51%|
| This paper | 2020–07      | combined    | Tranco 100K | 13,989 | 13.99%|
|         | – static       |             | 11,957   | 11.96%|
|         | – dynamic      |             | 12,194   | 12.19%|

therefore no longer ignore the potential impact of bot detection on their study.

Towards robust instrumentation. Our findings highlight the difficulties of deploying instruments via the page context. To improve robustness, we advocate moving the instruments outside of page scope. To achieve this, the debugger API could be leveraged. However, OpenWPM uses Selenium v3, which does not support this (planned for Selenium v4). Alternatively, instrumentation could be integrated in the browser’s source code. This would give great flexibility in hiding distinctive aspects of the browser fingerprint. This would also incur significant additional maintenance overhead slowing adoption of new browser versions. However, OpenWPM’s rate of adoption is already slow – the tradeoff may thus be worth it.

Advice for conducting a web measurement study. While the evaluation of our proof-of-concept is limited in scope, we still find significant differences in a variety of attributes. While studies that focus on the amount of traffic seem to be (for now) in the clear, studies that focus on audio/video files or web tracking via cookies must take bot detection into account (Table 8). Similarly, studies that automatically crawl beyond the front page will encounter more bot detectors (Table 1).

Ethics. Our work aims to make OpenWPM a more reliable measurement framework. We responsible disclosed our findings and shared fixes of the identified issues. This helps make OpenWPM less detectable, and therefore its results more reliable. Of course, a less detectable scraper may itself be abused. For attacking specific sites, our improvements do not greatly impact the attack surface: a less detectable OpenWPM is a fine tool for studying thousands of sites, but not for a targeted attack on a specific site. For attacks that span thousands of sites (e.g., clickfarming), our improvements do not help: disguising as a regular browser is insufficient to overcome contemporary defenses. For that, site-specific fingerprints are needed[72]. Thus, existing re-identification-based countermeasures (e.g., rate limiting) are not impacted.

Availability & responsible disclosure. Our stealth extension is available via GitHub.11 We disclosed our findings (both attacks and identifiable properties) to the OpenWPM developers. We are working towards having our fixes integrated into the framework.

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Table 11: Integration of Firefox releases into OpenWPM

| Firefox release date | OpenWPM integration date | Outdated |
|----------------------|--------------------------|----------|
| 95.0 12/07/21        | 0.18.0 12/16/21          | 69 days  |
| 94.0 11/02/21        |                          |          |
| 93.0 10/05/21        |                          |          |
| 92.0 09/07/21        |                          |          |
| 91.0 08/10/21        |                          |          |
| 90.0 07/13/21        | 0.17.0 07/24/21          | 11 days  |
| 89.0 06/01/21        | 0.16.0 06/10/21          | 9 days   |
| 88.0 04/19/21        | 0.15.0 05/10/21          | 48 days  |
| 87.0 03/23/21        |                          |          |
| 86.0.1 03/11/21      | 0.14.0 03/12/21          | 87 days  |
| 85.0 01/26/21        |                          |          |
| 84.0 12/15/20        |                          |          |
| 83.0 11/18/20        | 0.13.0 11/19/20          | 58 days  |
| 82.0 10/20/20        |                          |          |
| 81.0 09/22/20        |                          |          |
| 80.0 08/25/20        | 0.12.0 08/26/20          | 29 days  |
| 79.0 07/28/20        |                          |          |
| 78.0.1 07/01/20      | 0.11.0 07/09/20          | 8 days   |
| 77.0 06/03/20        | 0.10.0 06/23/20          | 20 days  |

if the webdriver property is checked via the navigator object. Table 12 lists our explored patterns. Finally, we manually checked a random subset to check pattern performance. Only one pattern still introduced false positives; all its matches were manually validated and false positives eliminated.

Table 12: Patterns evaluated in static analysis

| Pattern | false positives found |
|---------|-----------------------|
| webdriver | ✓                     |
| instrumentFingerprintingApis | -                    |
| getInstrumentJS | -                    |
| jsInstruments | -                    |
| (?<!_|-.)webdriver(?!_|-) | ✓                     |
| navigator.webdriver | -                    |
| navigator["\"]webdriver[""] \ | -                    |

D Previous studies relying on OpenWPM

Table 13 provides a detailed view on our analysis of previous peer-reviewed studies based on OpenWPM. Each category that applies to a study is marked with a “✓”. For those studies that measure certain aspects, but rely on out of bound mechanisms (e.g., by deploying a proxy) and do not rely on OpenWPM’s instrumentation are marked with a “◦”. Running modes are shortened in the table as follow: unspecified (u), native (n), headless (h), xvfb (x), docker (d), virtual machine (v). Papers that are not included in the seed list, but where added by us, are highlighted with a “⋆”.

18
| Year | Ref. | 1st Author | Mode | VM | Cookies | HTTP | JS | Scrolling | Clicking | Typing | Sub-pages | Anti-BD | BD |
|------|------|------------|------|----|---------|------|----|-----------|----------|--------|-----------|--------|----|
| 2014 | [2]  | Acar       | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [59] | Robinson   | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2015 | [28] | Englehardt | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [43] | Kranch     | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [7]  | Altaweel   | h    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [51] | Fruchter   | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2016 | [8]  | Andersdotter| u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [27] | Englehardt | x    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [71] | Starov     | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2017 | [53] | Miramirkhani| u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      |      |            |      |    |          |      |    |           |          |        | ✓         |        |    |
|      | [11] | Brookman   | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [57] | Reed       | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [54] | Olejnik    | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [50] | Maass      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [48] | Liu        | h    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [62] | Schmeiser  | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2018 | [32] | Goldfeder  | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [26] | Englehardt | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [9]  | Binns      | h    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [23] | Das        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [77] | van Acker  | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [22] | Dao        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2019 | [19] | Cozza      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [33] | Gomes      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [78] | van Eijk   | d    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [70] | Sørensen   | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [47] | Liu        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [56] | Mathur     | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [51] | Ramadorai  | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [52] | Mazel      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [6]  | Ali        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [61] | Samarasinghe| u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [49] | Maass      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [68] | Solomos    | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [76] | Vallina    | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [39] | Jonker     | h    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [74] | Urban      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [60] | Sakamoto   | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2020 | [29] | Fouad      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [18] | Cook       | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [81] | Yang       | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      |      |            |      |    |          |      |    |           |          |        | ✓         |        |    |
|      | [1]  | Acar       | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [42] | Koop       | d    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [52] | Zeber      | n/x | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [5]  | Ahmad      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [4]  | Agarwal    | h    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [73] | Urban      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [75] | Urban      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [53] | Pouryousef | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [30] | Fouad      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [66] | Sivan-Sevilla| u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [36] | Hu         | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [20] | Dao        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [69] | Solomos    | n    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [21] | Dao        | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
| 2021 | [13] | Calzavara  | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [58] | Rizzo      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [38] | Iqbal      | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      | [34] | Gößen*     | n    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |
|      |      |            |      |    |          |      |    |           |          |        | ✓         |        |    |
| 2022 | [14] | Cassel     | u    | ✓  | ✓       | ✓    | ✓  | ✓         | ✓        | ✓      |           |        |    |