A First Look at Android Apps' Third-party Resources Loading

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Abstract. Like websites, mobile apps import a range of external resources from various third-party domains. In succession, the third-party domains can further load resources hosted on other domains. For each mobile app, this creates a dependency chain underpinned by a form of implicit trust between the app and transitively connected third-parties. Hence, a such implicit trust may leave apps' developers unaware of what resources are loaded within their apps. In this work, we perform a large-scale study of dependency chains in 7,048 free Android mobile apps. We characterize the third-party resources used by apps and explore the presence of potentially malicious resources loaded via implicit trust. We find that around 94% of apps (with a number of installs greater than 500K) load resources from implicitly trusted parties. We find several different types of resources, most notably JavaScript codes, which may open the way to a range of exploits. These JavaScript codes are implicitly loaded by 92.3% of Android apps. Using VirusTotal, we classify 1.18% of third-party resources as suspicious. Our observations raise concerns for how apps are currently developed, and suggest that more rigorous vetting of in-app third-party resource loading is required.

1 Introduction

Mobile apps have become extremely popular [54], however, recently there has been a flurry of research [25] [31] exposing how many of these apps carry out misleading or even malicious activities. These acts range from low-risk (*e.g.,* usage of services and inter process communication which may drain the battery, CPU or memory) to high-risk (*e.g.,* harvesting data and ex-filtrating to third-parties [31].

We are interested in understanding the root source of this suspicious (or *malicious*) activity. Past work has treated this question as trivial—naturally, the root source of suspicious activity is the app's developer [25]. However, in this paper, we counter this assumption and shed light on the true complexity of suspicious app activity. We focus on the use of dynamically loaded *third-party* resources within apps. Mobile apps often load these resources from a range of third-party domains which include, for example, ad providers, tracking services,

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content distribution networks (CDNs) and analytics services. Although loading these resources is a well known design decision that establishes *explicit trust* between mobile apps and the domains providing such services, it creates complexity in terms of attribution. For example, it is not clear whether an app developer *knows* the third party resources are suspicious. This is further complicated by the fact that certain third-party code can further load resources from other domains. This creates a *dependency chain* (see Figure 1 for example), where the first-party app might not even be aware of the resources being loaded during its execution. This results in a form of *implicit trust* between mobile apps and any domains loaded further down the chain.

Consider the example `BBC News` [4] Android mobile app (cf. Figure 1) which loads JavaScript code from the `widgets.com` domain, which, upon execution loads additional content from another third-party, `ads.com`. Here, `BBC News` as the first-party, *explicitly* trusts `widgets.com`, but *implicitly* trusts `ads.com`. This can be represented as a simple dependency chain in which `widgets.com` is at level 1 and `ads.com` is at level 2 (see Figure 1). Past work tends to ignore this, instead, collapsing these levels into a single set of third-parties [21] [41].

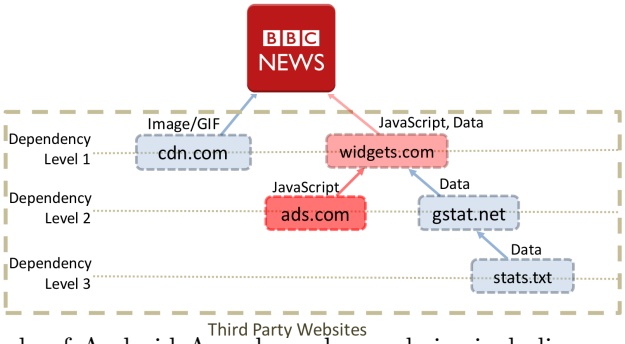


Fig. 1: Example of Android App dependency chain, including malicious third-party (in red). Here, Dependency Level 1 and Dependency Level ≥ 2 represent resources loaded from explicitly and implicitly trusted parties, respectively.

This, however, overlooks a vital security aspect for resources loaded by mobile apps. For instance, it creates a significant security challenge, as mobile apps lack visibility on resources loaded further down their domain's dependency chain. The dynamic nature of the content is loaded and the wide adoption of in-path traffic alterations [45][16] further complicates the issue. The potential threat should not be underestimated as errant active content (*e.g.,* JavaScript code) opens the way to a range of further exploits, *e.g.,* Layer-7 DDoS attacks [42] or malvertising [46] and ransomware campaigns [33].

In this work, we study dependency chains in Android apps. We use static and dynamic analysis to extract the URLs requested by apps and leverage our distributed crawling framework to retrieve apps' resource dependency chains. We then use VirusTotal API [32] to augment apps' dependency chains to characterize any suspicious resource loading. By analyzing 7,048 apps, we explore their implicit dependencies on third parties; we find that over 98.2% of apps

have dependency chains > 1, and therefore rely on an implicit trust model (§ 3). Although the majority (84.32%) of these have short chains of 4 and below levels, a notable minority (5.12%) have chains exceeding 5 levels. We also analyze different types of resource types and interestingly find JavaScript codes to be implicitly loaded by 92.3% of Android apps. This is perhaps due to app developers are unaware of the risks of implicitly trusting active content like JavaScript codes imported in WebView. Moreover, we inspect the categories of third-parties and find the predominance of the "Business" category across all dependency levels *i.e.,* 39.34% of all loaded resources at level 1, which increases to 40.54% at level 3, then to 51.4%, and so on. We also investigate the most occurring implicit third-parties and find `google-analytics.com` and `doubleclick.net` to be imported by 83.8% and 79.41%, respectively.

Although the above findings expose the analyzed Android apps to a new attack surface (as implicit trust makes it difficult for Android apps' owners or developers to vet third-parties), arguably, this alone does not create a security violation. Hence, we proceed to test whether or not these chains contain any malicious or suspicious third parties. To this end, we classify third-party domains into innocuous vs suspicious. Using several VirusTotal thresholds (which we refer to as VTscore (explained in § 2.5)), we find that a considerable fraction of the third-parties involved in the dependency chains is classified as suspicious. These perform suspicious activities such as requesting sensitive resources and sending HTTP(S) requests to known malicious domains. We find that 1.18% of third-parties are suspicious with a VTscore $\geq$ 10 (i.e. at least 10 AntiVirus services flagged them as malicious domains). This fraction naturally decreases when increasing the VTscore, for example with the VTscore of $\geq$ 40 the number of suspicious websites is 0.16% only. We then further investigate JavaScript code and find that more than half of the code (51%) implicitly trusted (i.e., loaded at trust level 2 and beyond) have a VTscore $\geq$ 30 which suggests high confidence in the security assessment. Finally, to foster further research, we release the dataset and scripts used in this paper to the research community: `https://mobapptrust.github.io/`.

2 Background and Methodology

Figure 2 presents an overview of the steps involved in analyzing apps' resource dependency.

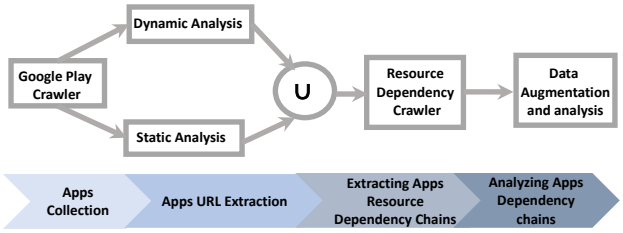


Fig. 2: Overview of our measurement methodology.

2.1 Third-party ecosystem

Third-parties extend an app's capabilities by providing useful content (*e.g.,* video, audio) and ways (*e.g.,* libraries and codes) to track users and deliver advertisements. Third-party services such as content delivery networks (CDNs), advertisers, and trackers have been around for years [38]. Recent years have seen apps relying on a wide range of third-party mobile ad and tracking services [31][48], typically fetched from ad aggregators such as `doubleclick.net` and AdMob through the ad libraries embedded in apps. Generally, an app developer registers with an ad aggregator, who provides the developer with a developer ID and an ad library which will be embedded in the app to fetch ads from other third-parties advertisers. The app developer is then paid by the ad provider based on the number of ad clicks or impressions, or both.

In the context of mobile advertising, the advertisers are parties who wish to advertise their products, the publishers are mobile applications (or their developers) that bring advertisements to the users. Ad networks or aggregators link the publishers to the advertisers, being paid by the latter and paying the former. Tapping on advertisements may lead users to content on Google Play or to web links. This often happens through a chain of several webpage redirections [30][40]. We generally refer to all these URLs in the webpage redirections as the redirection chain and the final webpage as the landing page. Ad networks themselves may participate in complex relationships with each other [30]. Certain parties, such as ad networks, run so-called ad exchanges where a given ad space is auctioned among several bidding ad networks so as to maximize profits for the publishers [14]. Ad networks also have syndication relationships with each other: an ad network assigned to fill a given ad space may delegate that space to another network. Such delegation can happen multiple times through a chain of ad networks and is visible in the redirection chains.

2.2 Collecting app metadata from Google Play

It is first necessary to collect a representative sample of mobile apps. As we wish to study the infiltration by suspicious third-parties, we strive to obtain a set of 'mainstream' apps (rather than fringe or malware related apps). Thus, we implement a Google Play crawler. This first obtains the app ID (or package name) for the top 50 apps listed within 10 Google Play categories: game, entertainment, business, communication, finance, tools, productivity, personalization, news & magazines, and education. Our crawler follows a breadth-first-search approach for any other app considered as *"similar"* by Google Play and for other apps published by the same developer. For each (*free*) app, we collect its metadata and executables (apks). We collect all metadata: number of downloads, category, average rating, negative/positive reviews, and developer's website.

We collected 10,000 *free* apps from Google Play of which we successfully analyze 7,048 apps. Due to obfuscation and protection against source code our static analysis tools (further detailed below in § 2.3) failed to decompile 2,469 apps. Similarly, 483 require *login* to interact with the apps' declared activities,

thus our dynamic analysis tools failed to analyze them. Overall, our corpus consists of 7,048 apps distributed across 27 different categories (collected in Dec 2018). For context, Figure 3 presents the number of apps we have with different ratings and a number of downloads. Our dataset also consists of apps that receive high user ratings: 70.7% of the apps have more than 4-star ratings and 72% of them have 500K+ downloads as depicted in Figure 3. These apps have 364,999,376 downloads (the sum of lower values of the installs). We argue this constitutes a reasonable sample of apps considered to be both mainstream and non-malicious in nature.

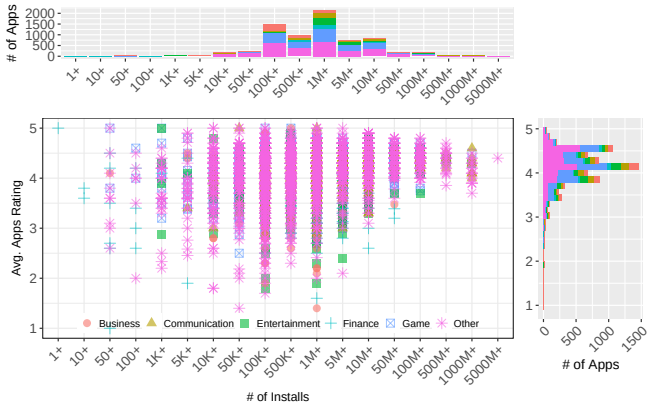


Fig. 3: An overview of analyzed apps' install and ratings on Google Play.

2.3 Extracting apps' resource dependency chains

It is next necessary to extract the third-party (web) resources utilized by each analyzed app. As depicted in Figure 2, we extract this set of URLs/domains in two ways: *First*, for each app, we use the Google Play Unofficial Python API [9] to download each app's executable, and use `ApkTool` [3]–a static analysis tool– to decompile them. We then leverage regular expressions to comprehensively search and extract embedded URLs/domains in the decompiled source code. *Second*, we use a dedicated testbed, composed of a smartphone that connects to the Internet via a computer configured as a WiFi access point (AP) with dual-stack support. The WiFi AP runs `MITMProxy` [10] to intercept all the traffic being transmitted between the mobile device and the Internet. This allows us to observe the resources loaded (or URLs/domains requested) by each app. To automate the execution of apps in our corpus, we leverage `MonkeyRunner` [11] to launch an app in our test mobile phones and to interact with an app by emulating user interactions such as clicking and swapping on all *activities* defined in the `AndroidManifest.xml` files. We exclude 483 apps from our analysis as they have only *login* activities defined in the AndroidManifest.xml files. To complete the execution and rendering of each activity, we enforce a 20-second waiting time and 400 seconds runtime session per app executing, on average, 35 different activities. For each app, we combine the list of URLs/domains extracted from the app's source code and the app's network traffic. The above two techniques

result in 414,387 URLs and 89,787 domains that correspond to 16,069 second-level domains.

2.4 Resource dependency dataset

Once we have the third-party resources for each analyzed app, we next strive to reconstruct the dependency chain. To this end, we build a crawling framework to collect apps' resource dependency chains. As mobile browsers have limited automation options and instrumentation capabilities, we modify the Chrome Headless crawler, detailed in [35], to imitate Google apps' WebViews. To ensure that we would see the correct mobile WebViews, leveraging previous work [18], our instrumentation involves: overriding the navigator object's user agent, OS platform, appVersion and appCodeName strings; and screen dimensions. Specifically, we emulate Chrome on Android, as it uses the same WebKit layout engine as the desktop Chrome used in the crawls. Recall that this covers the sequence of (JavaScript) resources that trigger further fetches.

For each of the 414,387 URLs identified, we then load and render it using our Chromium Headless crawler, detailed in [35]. This Chromium-based Headless [24] crawler renders a given URL/domain and tracks the resource dependencies by recording network requests sent to third-party domains. The requests are then used to reconstruct the dependency chain between each app and its requested URLs. Essentially, a dependency chain is constructed by analyzing each parent and child domain duple. We then extract the URL of the parent domain, the URL of the child domain, and the URL of the referrer. If the referrer differs from the parent, we add a branch from the parent to the referrer and then from the referrer to the child. Otherwise, if the parent is the referrer, we add a branch from the parent to the child. This is done for every parent and child tuple returned from our crawler. Note that each app can trigger the creation of multiple dependency chains. This process results in 414,387 dependency chains extracted (one per URL), creating a total set of 4,670,741 URLs.

Figure 1 presents an example of a dependency chain with 3 levels. *level 1* is loaded directly by the app, and is therefore explicitly trusted by it (*i.e.,* `BBC News`). *level 2* and *3*, however, is implicitly (or indirectly) trusted as the BBC News app may not necessarily be aware of their loading. For simplicity, we consider any domain that differs from the domain owned–obtained the domain from Google Play–by the analyzed app to be a third-party. More formally, to construct the dependency chain, we identify third-party requests by comparing the second level domain of the page (*e.g.,* `bbc.com`) to the domains of the requests (*e.g.,* `cdn.com` and `ads.com` via `widgets.com`).

Those with different second-level domains are considered third-party. We ignore the sub-domains so that a request to a domain such as `player.bbc.com` is not considered a third-party. Due to the lack of purely automated mechanism to disambiguate between site-specific sub-domains (*e.g.,* `player.bbc.com`) or country-specific sub-domains (*e.g.,* `bbc.co.uk`), `tldextract` [36] for this task. Moreover, we distinguish between first-party second-level domains, in which case the developer of an app also owns the domain, and third-party domains, which

include ad networks, trackers, social networks, and any other party that an app contacts. For instance, `twitter.com` is a first-party to the Twitter App but it is a third-party to BBC News.

2.5 Meta-data collection from VirusTotal

The above steps result in a dependency chain being created for each URL loaded by an app. As a major goal within our work is to identify potentially suspicious third-party resources, it is necessary to annotate these dependency chains with data about the potential risks. To achieve this, we leverage the VirusTotal public API to automatize our classification process. VirusTotal is an online solution that aggregates the scanning capabilities provided by 68 AV tools, scanning engines, and datasets. It has been commonly used in the academic literature to detect malicious apps, executables, software, and domains [31]. Upon submitting a URL, VirusTotal provides a list of scans from 68 anti-virus tools. We use the report API to obtain the VTscore for each third-party URL belonging to mobile apps in our dataset. Concretely, this score is the number of AV tools that flagged the website as *malicious* (max. 68). We further supplement each domain with their WebSense category provided by the VirusTotal's *record* API. During the augmentation, we eliminate invalid URLs (1.7%) in each dependency chain. Thus, we collect the above metadata for each second-level domain in our dataset. This results in a final sample of 4,675,173 URLs consisting of 89,787 unique domains from which we extract 16,699 unique second-level domains.

3 Analysis of Apps' Resource Dependency Chains

We begin by characterizing the resources imported by apps. We seek to determine if apps do, indeed, rely on implicit trust.

3.1 Characterizing apps' implicit trust

We analyze the resource loaded per app (resp. per category of apps) and measure the "depth" of implicit trust, *i.e.,* how many levels in the dependency chain an app loads resources from. Collectively, the 7,048 apps in our dataset make 4,670,901 calls to 414,387 unique external resources, with a median of 509 external resources per app. To dissect this, Table 1 presents the percentage of apps that both explicitly and implicitly trust third-party resources. We separate apps into their popularity, based on their number of downloads on the Play store.

Table 1 shows that the use of third-party resources is extremely common. 98.2% of explicitly trust third-parties at least once, with 22.1% importing externally hosted JavaScript code. Moreover, around 95% of the apps do rely on *implicit* trust chains, *e.g.,* they allow third-parties to load further third-parties on their behalf. This trend is already well-known [30] in the web context; here we confirm it for mobile apps. Note, the propensity to form dependency chains (≥ 2) is marginally higher in more popular apps; for example, 94% of apps with

a number of installs $\geq$ 500K have dependency chains compared to 86% of apps with a number of installs $\leq$ 100K.

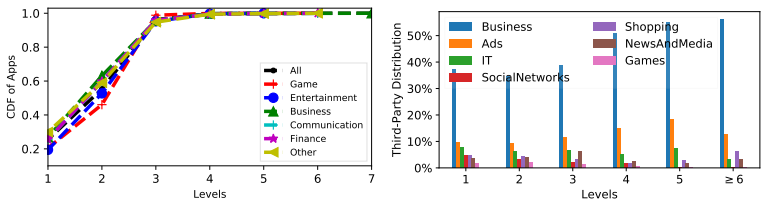
	Number of Installs						
	1-5B (7048)	1-10K (119)	10K-100K (391)	100K-500K (1456)	500K-5M (3069)	5M-50M (1588)	50M-5B (425)
Apps that trust at least one third-party which loads:							
Any Resources:							
Explicitly (Lvl. 1)	98.2%	89.9%	93.6%	97.1%	98.2%	99.0%	99.3%
Implicitly (Lvl. $\geq$ 2)	95%	82%	**86%**	93%	**94%**	96%	98%
JavaScript:							
Explicitly	22.1%	26.7%	25.3	23.1%	20.6%	21.7%	18.1%
Implicitly	92.3%	65.5%	79.3%	90.9%	92.9%	94.3%	92.0%

Table 1: Overview of the dataset for different ranges of a number of apps' install. The rows indicate the proportion of a number of app installs that explicitly and implicitly trust at least one third-party (*i*) resource (of any type); and (*ii*) JavaScript code.

We next inspect the *depth* of the dependency chain. Intuitively, long chains are undesirable as they typically have a deleterious impact on resource load times [55] and increase attacks surface, *e.g.,* drive-by downloads [19] [17], malware and binary exploitation [51] [47] [52] [44], or phishing attacks [56].

Figure 4a presents the CDF of chain level for all apps in our dataset. For context, apps are separated into their sub-categories.[3] It shows that 84.32% of the analyzed apps create chains of trust of level 4 or below. Overall, we find that all mobile apps import ≈5.12% of their external resources from level 5 and above. However, there is also a small minority that dramatically exceeds this level. In the most extreme case, we see `AntiVirus 2019` [2], having 1M+ downloads and average rating 4.2, with a chain containing 7 levels, consisting of mutual calls between `pubmatic.com` (online marketing) and `mathtag.com` (ad provider). Other notable examples include `RoboForm Password Manager` [13] (productivity app with 500K+ downloads and average rating 4.3), `Borussia Dortmund` [5] (sport, 1M+, 4.5), and `Cover art Evite: Free Online & Text Invitations` [7] (social, 1M+, 3.9) have a maximum dependency level of 7. We argue that these complex configurations make it extremely difficult to reliably audit such apps, as an app cannot be assured of which objects are later loaded. Briefly, we also note that Figure 4b reveals subtle differences *between* different categories, according to WebSense categorization (cf. § 2.5), of third-party domains. For example, those classified as Business and Adverts are most likely to be loaded at level 1; this is perhaps to be expected, as many ad brokers naturally serve and manage their own content. In contrast, Social Network third-parties (*e.g.,* Facebook plug-ins) are least likely to be loaded at level 1.

[3] We include the most popular categories and group subcategories (Arcade, Action, Adventure, Board, Card, Casino, Casual, Educational, Music, Puzzle, Racing, Role Playing, Simulation, Strategy, Sports, Trivia, and Word) to 'Game'.



(a) (b)

Fig. 4: (a) CDF of dependency chain levels (broken down into categories of apps); and (b) distribution of third-parties across various categories and levels.

3.2 Characterizing the types of resources

The previous section has confirmed that a notable fraction of apps creates dependency chains with (up to) 7 levels. Next, we inspect the types of imported resources within these dependency chains. For analyzed (categories of) apps at each level of the resource dependency chain, we classify the types of loaded resources into six main types: Data (consisting of HTML, XML, JSON, plain text, and encoded files), Image, JavaScript code, CSS/Fonts, Audio, and Video. We were unable to classify 5.28% of resources loaded by the analyzed apps. On a closer look, we find that 98% of these uncategorized resources were imported from 242 unique, static IP addresses via WebSockets while 2% of the uncategorized resources were requested from localhost (127.0.0.1).

Table 2 presents the volume of each resource type imported at each level in the trust chain. We observe that the make-up of resources varies dramatically based on the level in the dependency chain. For example, the fraction of images imported tends to increase—this is large because third-parties are in turn loading images (*e.g.,* for adverts). In contrast, the fraction of JavaScript codes decreases as the level in the dependency chain increases: 27.2% of resources at level 2 are JavaScript codes compared to just 11.92% at level 5. This trend is caused by the fact that new levels are typically created by JavaScript execution (thus, by definition, the fraction of JavaScript codes must be deplete along the chain). However, it remains at a level that should be of concern to app developers as this confirms a significant fraction of JavaScript code is loaded from potentially unknown implicitly trusted domains.

Lev.	Total	Data	Image	JS	CSS/Font	Audio	Video	Uncategorized
1	315,217	91.76%	3.74%	1.4%	0.06%	0.21%	0.07%	2.76%
2	4,040,882	10.22%	45.55%	27.2%	13.12%	0.06%	0.17%	3.53%
3	171,035	8.13%	33.11%	23.62%	5.36%	0.03%	0.01%	29.75%
4	63,179	1.6%	24.16%	14.32%	0.48%	0%	0%	59.43%
5	6,116	14.34%	18.35%	11.92%	8.19%	0%	0%	47.2%
≥ 6	383	7.31%	26.11%	1.04%	0%	0%	0.52%	65.01%

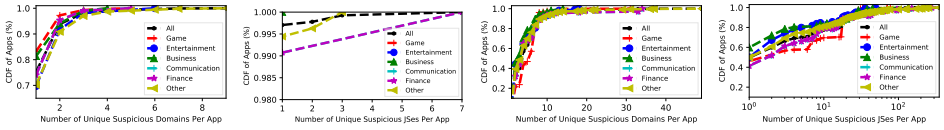
Table 2: Breakdown of resource types requested by the analyzed apps across each level in the dependency chain. The total column refers to the number of resource calls made at each level. Here *JS* represents the JavaScript code category of imported resources.

To build on this, we also inspect the *categories*, taken from WebSense (see § 2.5 for details), of third-party domains hosting these resources. Figure 4b presents the make-up of third-party categories at each level in the chain. It is clear that, across all levels, Business and Advertisement domains make up the bulk of third-parties. We also notice other highly demanded third-party categories such as Business, Ads, and IT. These are led by well-known providers, *e.g.,* `google-analytics.com` (web-analytics–grouped as in business category as per VirusTotal reports) provides resources to 83.78% of the analyzed apps. This observation is in line with the fact that 81.4% of the analyzed apps embed Google ads and analytic service libraries. The figure also reveals that the distributions of categories vary slightly across each dependency level. For example, 37.7% of all loaded resources at *level 1* come from Business domains compared to 39.1% at *level 3*, *i.e.,* overall, the proportion increases across dependency levels. We also observe similar trends for resources loaded from Ads and IT (*e.g.,* web hosting) domains.

In contrast, social network third-parties (*e.g.,* Facebook) are mostly presented at *level 1* (4.89%) and 2 (3.26%) with a significant drop at *level 3*. The dominance of Business and Advertisements is not, however, caused by a plethora of Ads domains: there are far fewer Ads domains than Business (see Table 4). Instead, it is driven by a large number of requests for advertisements: even though Ads domains only make up 9.01% of third-parties, they generate 13.58% of resources. Naturally, these are led by major providers. Importantly, these popular providers can trigger further dependencies; for example, 79.41% of apps leverage `doubleclick.net` which imports 11% of its resources from further implicitly trusted third-party domains. This makes such third-parities means for online fraudulent activities and ideal propagator of "malicious" resources for any other domains having implicit trust in it [39].

4 Analyzing Malicious Resource Dependency Chains of Apps

The previous section has shown that the creation of dependency chains is widespread, and there is therefore extensive implicit trust within the mobile and third-party app ecosystem. This, however, does not shed light on the activity of resources within the dependency chains, nor does it mean that the implicit trust is abused by third-parties. Thus, we next study the existence of *suspicious* third-parties, which could lead to abuse of the implicit trust. Within this section, we use the term *suspicious* (to be more generic than malicious) because VirusTotal covers activities ranging from low-risk (*e.g.,* sharing private data over unencrypted channels) to high-risk (malware).



(a) Level 1 (b) Level 1 (c) Level ≥ 2 (d) Level ≥ 2

Fig. 5: CDFs of number of unique suspicious domains contacted and JavaScript codes downloaded by apps (broken down into apps' categories) at explicit level (Level = 1) and implicit level (Level ≥ 2).

4.1 Do apps load suspicious third-parties?

First, we inspect the fraction of third-party domains that trigger a warning by VirusTotal. From our third-party domains, in Table 4, 14.95% have a VTscore of 1 or above, *i.e.,* at least one virus checker classifies the domain as suspicious. If one treats the VTscore as a ground truth, this confirms that popular websites do load content from suspicious third-parties via their chains of trust. However, we are reticent to rely on VTscore = 1, as this indicates the remaining 67 virus checkers did not flag the domain[4]

Table 4 shows the fraction of third-parties that are classified as suspicious using several VTscore thresholds. For context, we separate third-parties into their respective categories. If we classify any resource with a VTscore of ≥ 10 as suspicious, we find that 1.18% (188) of third-party domains are classified as suspicious with 1.36% of all resource calls in our dataset going to these third-parties. Notably this only drops to 0.59% with a *very* conservative VTscore of ≥ 20. We observe similar results when considering thresholds in the [5...50] range. We therefore conservatively refer to domains with a VTscore ≥ 10 as suspicious in the rest of this analysis.

4.2 Do apps' dependency chains contain suspicious parties?

The above has shown that apps do load suspicious resources. We next inspect where in the dependency chains these resources are loaded at. Additionally, we inspect apps that inherit suspicious JavaScript resources from the explicit and various implicit levels. We focus on JavaScript codes as active web content that poses great threats with significant attack surfaces consisting of vulnerabilities related to client-side JavaScript when executed in apps WebView mode, such as cross-site scripting (XSS) and advanced phishing [37][56].

Figure 5 depicts the cumulative distributions (CDFs) of number of unique suspicious domains and JavaScript codes per (different categories of) apps. Although we do not observe significant differences among the various apps' categories, however, from the trends in the sub-figures, interestingly, we find that the majority of (resp. JavaScript codes) resources classified as suspicious are located at level 2 in the dependency chain (*i.e.,* implicitly trusted by the app).

Overall, we find that 21.46% (1,513) of the analyzed apps import at least one resource from a suspicious domain with VTscore ≥ 10. Table 5 shows well-known apps, ranked according to the number of unique suspicious third-parties in their chain of dependency. We note that the popular (most vulnerable) apps belong to various categories such as Productivity, Finance, Education, and Communication. This indicates that there is no one category of domains that inherits suspicious JavaScript codes. However, we note that the first mobile apps categorized as "Productivity" represent the majority of most exposed domains at level $\geq$2, with 16% of the total number of apps implicitly trusting suspicious JavaScript codes belonging to the Business Category, with the distant second being the "Communication" Category and third the "Finance" category. The

[4] Diversity is likely caused by the databases used by the various virus checkers [15].

number of suspicious JavaScript codes loaded by these apps ranges from 3 to 25 JavaScript codes. We note the extreme case of 35% app *implicitly* importing at least 6 unique suspicious JavaScript programs from 3 unique suspicious domains. Moreover, we observe at most 7 unique third-parties (combining both explicit and implicit level) that is a cause of suspicious JavaScripts in mobile apps. This happens for Package Tracker [12], with over 1M install and 4.6 average rating on Google Play, having third-party domains such as `nrg-tk.ru`, `yw56.com.cn`, `bitrix.info`, `fundebug.com`, and `ghbtns.com`.

4.3 How widespread are suspicious parties?

We next inspect how "popular" these suspicious third-parties are at each position in the dependency chain, by inspecting how many Android apps utilize them. Figure 6 displays the CDF of resource calls to third-parties made by each app in our dataset. We decompose the third-party resources into various groups (including total *vs.* suspicious). As mentioned earlier, we take a conservative approach and consider a resource suspicious if it receives a VTscore ≥ 10.

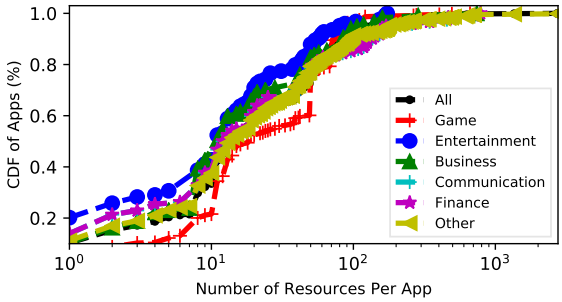


Fig. 6: CDF of resources loaded per app from various categories of third-parties.

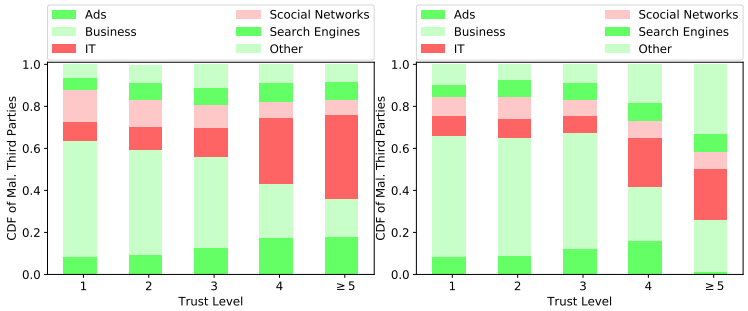
The figure reveals that suspicious parties within the dependency chains are commonplace: 12.76% of all apps contain at least 3 third-parties classified as suspicious in their dependency chain. Remarkably, 21.48% of apps load resources from third-parties at least once. Hence, even though only 9.01% of third-party domains are classified as suspicious, their reach covers nearly one-fifth of the apps (indirectly via implicit trust).

This is a product of the power-law distribution of third-party "popularity" across Android apps: The top 20% of third-party domains cover 86% (3,650,582) of all resource calls. Closer inspection shows that it is driven by prominent third-parties: `github.io` and `tapjoy.com`, and `baidu.com` obtaining, during the measurement period, VTscore of 11, 18, and 21 suggesting a high degree of certainty of being suspicious. For instance, in the case of "Egypt News Moment by Moment" [6] which loaded JavaScript resources from `github.io`, it was actually caused by `github.io` loading another third-party, `ghbtn.com`, which is known to be abused by attackers for hosting malware [8] and phishing kits [22].

4.4 Which suspicious third-parties are most prevalent?

Next, we inspect in, Table 6, the top 10 most frequently encountered suspicious third-party domains that are providing suspicious JavaScript resources to first-parties (as opposed to the most exposed Android apps domains shown earlier in Table 5). We rank these suspicious third-party domains according to their prevalence in the Web ecosystem and further decompose our analysis at explicit and implicit levels in the table. We found `github.io` is the most called domain. Interestingly, we find several suspicious third-party domains from the Top 100 Alexa ranking. For instance, `baidu.com`, a search engine website mostly geared toward East-Asian countries has been used by 253 apps and is ranked 4 by Alexa. This domain is found to be one of the most prevalent suspicious third-party domains at both level 1 (140 apps) and levels ≥ 2 (113 apps). An obvious reason for this domain's presence is because of other infected (malware-based) apps that try to authenticate users from such domains [43]. Others such as `tapjoy.com` and `baidu.com` are also among the most prevalent third-party domains at level 1. These websites were reported to contain malware in their JavaScript codes [20] and suggest users promote [49] and install potentially unwanted programs [1].

While it is *not shown in the table*, we also note the presence of `qq.com`, a Chinese Search Engine ranked high by Alexa. This is among the top 10 most encountered suspicious third-party domains, as defined by 13 AV tools within VirusTotal. Closer inspection reveals this is likely due to repeated instances of insecure data transmission, use of `qq.com` fake accounts for malware manifestation and for data encryption Trojans [34] [26] [53].



(a) All Apps (b) Entertainment Apps

Fig. 7: Distribution of calls to suspicious third-party domains (VT score ≥ 10) per category at each level, for all (Fig. 7a) and Entertainment (Fig. 7b) apps.

4.5 At which level do suspicious third-parties occur?

Next, by inspecting the location(s) in the dependency chain where the malicious third-parties are situated and the *types* of apps that load them, we analyze the impact of suspicious resources loaded on mobile apps. This is vital as implicitly trusted (level ≥ 2) resources are far more difficult for an app developer (or owner) to remove—they could, of course, remove the intermediate level 1 resource, but this may disrupt their own business activities.

Table 3 presents the proportion of apps that import at least one resource with a VTscore ≥ 10. We separate resources into their level in the dependency chain. Interestingly, the majority of resources classified as suspicious are located at level 1 in the dependency chain (*i.e.,* they are explicitly trusted by the app). 41.2% of the analyzed apps containing suspicious third-parties are "infected" via level 1. This suggests that the app developers are not entirely diligent in monitoring their third-party resources and may purposefully utilize such third-parties [28].

4.24% of the analyzed apps import at least 11 resources from suspicious via *implicit* trust (*i.e.,* level ≥ 2). In these cases, the Game developers are potentially unaware of their presence. The most vulnerable category is Games: 23.34% of Game apps import *implicitly* trusted resources from level 2 with a VTscore ≥ 10. Notably, among the 78 Game apps importing suspicious JavaScript resources from trust level 2 and deeper, we find 41 apps loading advertisements from `adadvisor.net`. One possible reason is that ad-networks could be infected, or victimized with malware to perform malvertising [39][50] or binary exploitation [51][47].

	All Apps		**Games Apps**		**Entert. Apps**		**Business Apps**		**Comm. Apps**	
Lv.	All	JS	All	JS	All	JS	All	JS	All	JS
1	41.20%	37.37%	55.40%	43.43%	53.61%	47.20%	49.23%	45.38%	47.41%	45.25%
2	4.24%	1.29%	23.34%	4.53%	10.09%	3.50%	7.53%	3.21%	8.09%	3.05%
3	1.01%	0.13%	1.59%	0.40%	3.26%	0.18%	1.070%	0.29%	2.20%	0.10%
4	0.11%	$\leq 0.1\%$	0.51%	$\leq 0.1\%$	0.80%	$\leq 0.1\%$	0.60%	$\leq 0.1\%$	0.40%	$\leq$0.001%
≥ 5	$\leq 0.10\%$	0	$\leq$0.001%	$\leq 0.1\%$	$\leq$0.001%	$\leq 0.1\%$	$\leq$0.001%	$\leq 0.1\%$	$\leq$0.001%	0.00%

Table 3: Proportion of apps importing resources classified as suspicious (with VTscore ≥ 10) at each level.

Similar, albeit less extreme, observations can be made across Entertainment (abbreviated as Entert. in Table 3) and Business apps. Briefly, Figure 7 displays the categories of (suspicious) third-parties loaded at each level in the apps' dependency chains — it can be seen that the majority are classified as Business according to WebSense domain classification (cf. Section 2.5). This is, again, because of several major providers classified as suspicious such as `comeet.co` and `dominionenergy.com`. Furthermore, it can be seen that the fraction of advertisement resources also increases with the number of levels due to the loading of further resources (*e.g.,* images).

We next strive to quantify the level of suspicion raised by each of these JavaScript programs. Intuitively, those with higher VTscores represent a higher threat as defined by the 68 AV tools used by VirusTotal. Hence, Figure 8 presents the cumulative distribution of the VTscores for all JavaScript resources loaded with VTscore ≥ 1. We separate the JavaScript programs into their location in the dependency chain. A clear differences can be observed, with level 2 obtaining the highest VTscore (median 28). In fact, 51% of the suspicious JavaScript resources loaded on trust level 2 have a VTscore > 30 (indicating *very* high confidence).

Figure 9 also presents the breakdown of the domain categories specifically for suspicious JavaScript codes. Clear trends can be seen, with IT (*e.g.,* `dynaquestpc.com`), News and Media (*e.g.,* `therealnews.com`), Entertainment (*e.g.,* `youwatchfilm.net`) and Business (*e.g.,* `vindale.com`) are dom-

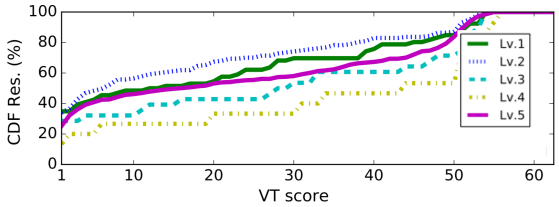


Fig. 8: CDF of suspicious JavaScripts (VTscores ≥ 1) at different levels in the chain.

inating. Clearly, suspicious JavaScripts cover a broad spectrum of activities. Interestingly, we observed that 63% and 66%, respectively, of IT and News & Media JavaScript codes, are loaded from level ≥ 2 in contrast to 17% and 25% of JavaScript code from Social Networks and Streaming loaded at *level 1*.

We next strive to quantify the level of suspicion raised by each of these JavaScript programs. Intuitively, those with higher VTscores represent a higher threat as defined by the 68 AV tools used by VirusTotal. Hence, Figure 8 presents the cumulative distribution of the VTscores for all JavaScript resources loaded with VTscore ≥ 1. We separate the JavaScript programs into their location in the dependency chain. A clear difference can be observed, with level 2 obtaining the highest VTscore (median 32). In fact, 78% of the suspicious JavaScript resources loaded on trust level 2 have a VTscore > 52 (indicating *very* high confidence).

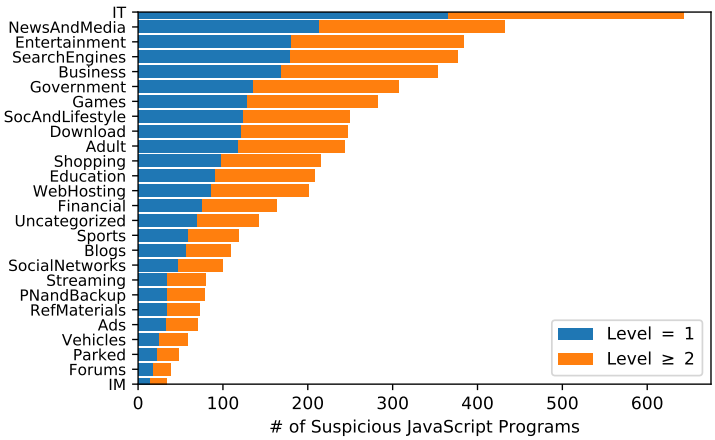


Fig. 9: Breakdown of suspicious JavaScript resources based on the category of the domain.

This is a critical observation since as mentioned earlier, while suspicious third-parties at level 1 can be ultimately removed by apps' developers if flagged as suspicious, this is much more difficult for *implicitly* trusted resources further along the dependency chain. If the intermediate (non-suspicious) *level 1* resource is vital for the webpage, it is likely that some operators would be unable or unwilling to perform this action. The lack of transparency and the inability to perform a vetting process on implicitly trusted loaded resources further complicates the issue. It is also worth noting that the VTscore for resources loaded

further down the dependency chain is lower (*e.g., level 4*). For example, 92% of level 2 resources receive a VTscore below 3. This suggests that the activity of these resources is more contentious, with a smaller number of AV tools reaching a consensus.

5 Related Work

We examine literature that measures third-party ecosystems on the web [30][29] and mobile platforms [48]; then review the security and privacy implication of loading resources from third-parties and illuminate on the chain of resource loading. Previous works analyzed the presences of third-party JavaScript libraries and ill-maintained external web servers making exploitation via JavaScript trivial [41]. Lauinger *et al.* led a further study, classifying sensitive libraries and the vulnerabilities caused by them [37]. Gomer *et al.* analyzed users' exposure to third-party tracking in the context of search queries, showing that 99.5% of users are tracked by popular trackers within 30 clicks [23]. Hozinger *et al.* found 61 third-party JavaScript exploits and defined three main attack vectors [27]. Our work differs quite substantially from these studies in that we are not interested in the third-party JavaScript code itself, nor the simple presence of third-party tracking domains embedded in tweets or in a webpage. Instead, we are interested in *how* mobile apps' users are exposed to third-parties and the presence of third-parties in the redirect chain. In contrast to our work, these prior studies ignore the presence of chains of resource loading and treat all third-parties as "equal", regardless of where they are loaded when users click on a given URL embedded in a tweet or webpage.

Kumar *et al.* [35] characterized websites' resource dependencies on third-party services. In line with our work, they found that websites' third-party resource dependency chains are widespread. This means, for example, that 55% of websites, among Alexa top 1M, are prevented from fully migrating to HTTPS by the third-parties that provide resources to them. More related work is Ikram *et al.* [30], who perform a large-scale study of suspicious resource loading and dependency chains in the Web, and around 50% of first-party websites render content that they did not directly load. They also showed that 84.91% of websites have short dependency chains (below 3 levels). The study reported that 1.2% of these suspicious third-parties have remarkable reach into the wider Web ecosystem. To the best of our knowledge, we are the first to characterize the chains of resource loading of mobile apps. Moreover, we also characterize the role of apps' suspicious resource loading. We suggest that more rigorous vetting of in-app third-party resources is required.

6 Concluding Remarks

This paper explored dependency chains in Android apps. Focusing on how external resources are loaded by mobile apps, we found that over 98.2% of apps *do* rely on implicit trust. Although the majority (70.91%) of the analyzed apps have short chains, we found apps with chains up to 7 levels of dependency. Perhaps unsurprisingly, the most commonly encountered *implicitly*

trusted third-parties are well-known analytics services and ad-networks domains (*e.g.,* `google-analytics.com` and `doubleclick.net`), however, we also observed various less common domains to be implicitly trusted third-parties. In our future work, we wish to perform longitudinal measurements to understand how these metrics of maliciousness evolve over time. We are particularly interested in understanding the (potentially) ephemeral nature of threats. To provide apps' users better control of their privacy and to facilitate secure resource loading, we also aim to investigate ways to automatically identify and sandbox suspicious parties in the resource dependency chains to alert users to security vulnerabilities (resp. HTTPS downgrades) of at each level of dependency chains.

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Category	Third-parties	Total Calls	Suspicious JS	VTScore ≥ 1		VTScore ≥ 5		VTScore ≥ 10		VTScore ≥ 20		VTScore ≥ 40	
				Num.	Vol.	Num.	Vol.	Num.	Vol.	Num.	Vol.	Num.	Vol.
Business	5,073 (33.43%)	1,030,635	63,970 (6.21%)	14.75%	47.59%	1.70%	2.75%	1.13%	1.17%	0.61%	0.22%	0.12%	0.09%
Ads	1,367 (9.01%)	623,261	100,843 (16.18%)	24.58%	60.65%	2.93%	5.36%	1.54	5.03%	0.59%	0.08%	0.08%	0.01%
IT	1,173 (7.73%)	41,841	887 (2.12%)	13.98%	14.54%	1.62%	3.42%	0.68%	1.61%	0.26%	0.09%	0%	0%
Shopping	607 (4.0%)	137,686	990 (0.72%)	13.51%	12.01%	1.98%	0.37%	1.32%	0.17%	1.15%	0.13%	0.66%	0.12%
NewsAndMedia	549 (3.62%)	76,566	1,205 (1.57%)	15.12%	28.86%	3.28%	0.94%	2.37%	0.93%	1.09%	0.14%	0.18%	0.03%
Social Networks	246 (1.62%)	160,789	5,033 (3.13%)	19.51%	85.77%	1.63%	0.59%	0.81%	0.59%	0.81%	0.59%	0%	0%
Games	244 (1.61%)	27,419	358 (1.30%)	16.39%	16.40%	2.46%	3.11	1.64%	1.96%	1.23%	1.93%	1.23%	1.93%
Others	5,916 (38.99%)	2,656,419	213,604 (8.04%)	12.98%	89.83%	1.81%	1.066%	1.12%	0.65%	0.50%	0.60%	0.15%	0.027%
Total	15,175 (100%)	4,670,741	386,890 (8.28%)	14.95%	73.69%	1.93%	2.03%	1.18%	1.36%	0.59%	0.44%	0.16%	0.06%

Table 4: Overview of suspicious third-parties in each category. **Col.2-4:** number of third-party websites in different categories, the number of resource calls to resources, and the proportion of calls to suspicious JavaScript code. **Col.5-9:** Fraction of third-party domains classified as suspicious (*Num.*), and fraction of resource calls classified as suspicious (*Vol.*), across various VTscores (i.e., ≥ 1 and ≥ 40).

Unique Suspicious Domains (and JSes) at Level = 1							
#	App	Cat.	Rat.	Insta.	Dom.	JSes	Chain len.
1	Dashlane Pass. Manag.	Prod.	4.6	1M+	9	3	7
2	BPI	Fina.	4.3	1M+	7	4	5
3	Korean Dictionary	Educ.	4.2	100K+	7	5	6
4	RoboForm Pass. Manag.	Prod.	4.3	500K+	7	4	7
5	Bane Voice Changer	Enter.	3.4	1M+	6	2	4
Unique Suspicious Domains (and JSes) at Level ≥ 2							
#	App	Cat.	Rat.	Insta.	Dom.	JSes	Chain len.
1	Package Tracker	Prod.	4.6	1M+	37	34	4
2	SGETHER Live Stream.	Vid. Play.	4.0	1M+	36	252	5
3	Opera Browser	Comm.	4.4	100M+	34	64	5
4	Adrohelm Antivirus	Comm.	4.2	1M+	34	48	7
5	NFL Game Centre	Game	4.1	50M+	31	34	3

Table 5: Top 5 most exposed apps (with VTscore ≥ 10) ranked by the number of unique suspicious domains.

Prevalence of Third-parties at Level = 1					
#	Third-party Domain	Alexa Rank	VTscore	# Apps	Category
1	`github.io`	50	11	769	IT
2	`tapjoy.com`	47,720	18	199	IT
3	`baidu.com`	4	21	140	SearchEngine
4	`oracle.com`	825	10	39	IT
5	`dominionenergy.com`	16,757	12	31	Business
Prevalence of Third-parties at Level ≥ 2					
1	`baidu.com`	4	21	113	SearchEngine
2	`sil.org`	64,483	16	17	Ads
3	`comeet.co`	87,766	13	117	Business
4	`cloudfront.net`	264	11	12	WebHosting
5	`amazonaws.com`	1,597	10	8	WebHosting

Table 6: Top 5 most prevalent suspicious third-party domains (VTscore ≥ 10) on level 1 and level ≥ 2 providing resources to Apps. The number of apps (# Apps) having the corresponding suspicious third-party domain in their chain of dependency.