

# Piecing Together App Behavior from Multiple Artifacts: A Case Study

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**Abstract**—Recent research in mobile software analysis has begun to combine information extracted from an app’s source code and marketplace webpage to identify correlated variables and validate an app’s quality properties such as its intended behavior, trust or suspiciousness. Such work typically involves analysis of one or two artifacts such as the GUI text, user ratings, app description keywords, permission requests, and sensitive API calls. However, these studies make assumptions about how the various artifacts are populated and used by developers, which may lead to a gap in the resulting analysis. In this paper, we take a step back and perform an in-depth study of 14 popular apps from the Google Play Store. We have studied a set of 16 different artifacts for each app, and conclude that the output of these must be pieced together to form a complete understanding of the app’s true behavior. We show that (1) developers are inconsistent in where and how they provide descriptions; (2) each artifact alone has incomplete information; (3) different artifacts may contain contradictory pieces of information; (4) there is a need for new analyses, such as those that use image processing; and (5) without including analyses of advertisement libraries, the complete behavior of an app is not defined. In addition, we show that the number of downloads and ratings of an app does not appear to be a strong predictor of overall app quality, as these are propagated through versions and are not necessarily indicative of the current app version’s behavior.

## I. INTRODUCTION

The use of mobile devices has created an enormous and lively marketplace for application development and deployment [1]–[4]. A developer can create a mobile application (or *app*) and provide it for users to download with only a small monetary investment [5], [6]. Apps exist to help users with almost any conceivable task. For instance, to track finances, provide meta-data about products when shopping, manage health, or play games (either alone or with friends). Millions of apps are found in marketplaces like the Google Play store [7], yet this type of distributed development comes with some downsides [8]–[11]. For the user who is concerned about application quality, it is difficult to discern what an app actually does [12], or to know if one can trust that it won’t perform malicious acts [13]–[15]. If an unexpected behavior occurs, it may not be clear if this is intended or is a fault – without a formal specification [16], [17], it is not possible to reliably check the behavior of these apps [18].

There are no formal requirements that must be adhered to when uploading an app to a marketplace [3], [9], [19], and no set standards for how to describe and document exactly how an

app is supposed to behave [20], [21]. The marketplaces provide ample space for developers to upload this information, but as we have learned, the structure for documentation is loose and its use open to choice and style [22], [23]. For instance, a developer can write a complete natural language description of their app, or they can provide screenshots or videos – or use a mixture [24]. They might instead, rely on the crowd and provide only a brief description, expecting users to comment on the other behavior within their reviews [25]–[27]. Some hints can be inferred about an application’s intention [28], such as the request for user permissions [29] to utilize particular resources (e.g. a camera), however, some apps use alternative mechanisms that rely on other apps (and their permissions) to access these resources (e.g. an app might use a camera Intent to utilize a camera via another app and this would not require explicit user permissions [30]), or they may over request, meaning that the user has no real idea of what the actual behavior will be [31]. Having such flexibility makes the release of new apps easy on the developer, however it means that users have incomplete information, and may end up surprised later. Even the use of a simple mechanism such as user reviews seems to be open to interpretation, since as we have learned, reviews from one version of an app appear to follow it to the next version. New faulty behavior, or malicious intent will not be exposed [32].

Recent research has focused on ways to automatically extract particular types of app behavior, such as those that might violate user privacy or that may indicate the existence of malware or stealthy methods [14], [33]. Other research has looked at ways to measure the amount of trust one should have in an app (by rating developers, comments, etc.) [34]. But most of these approaches use limited information. For instance, there has been work on finding mismatches between the online descriptions with the requested permissions [35], [36]. While this provides some notion of intended vs. hidden behaviors, we have learned that neither information source gives complete and accurate information. Other research has focused on comparing descriptions vs. API calls, however there is often a lot of *dead code* in the form of API calls leading to a large overapproximation [31]. Other analyses remove advertisement or analytic libraries [37], [38], for simplification. We have learned that the external libraries often have their own behavior, and require their own permissions –

and that they should not be ignored. Finally, there has been work on comparing user ratings, descriptions and permissions, but this is only a partial view [25], [26]. While all of these approaches extract important behavioral information, and each provides a useful analysis technique, they often target specific data elements which may expose only a subset of app behavior.

In this paper, we take a step back and ask what information should be utilized and pieced together to complete the puzzle of an app's true specification. We believe that this question is important, yet has not been previously answered. We present an in-depth case study on 14 highly downloaded apps from differing domains. We quantify the different sources of information that the developers use and look for inconsistencies between them. We synthesize these findings into a set of observations that should be used moving forward to provide a way to piece together the puzzle of understanding app behavior. The contributions of this work are:

- (1) A case study on a set of 14 apps that identifies where app specifications are contained and how they are used.
- (2) A synthesis of what we have learned that can provide a roadmap for extracting and combining information to develop the true specification of an app.

In the next section we provide some background on Android and present related work. In Sections III and IV we present our case study and discussion. We end with conclusions and future work (Section V).

## II. BACKGROUND AND RELATED WORK

Unlike traditional software applications that come bundled with extensive user guides, reference manuals, troubleshooting guides, etc., mobile apps are rarely supplied with such detailed artifacts. Instead, where they lack in providing extensive documentation and manuals, they attempt to make up for with a variety of concise artifacts, such as *Description*, *Reviews*, *What's New*, *Number of Installs*, *Platform Requirements*, *Content Rating*, *Permissions*, *Vendor Name*, *Category*, *Developer Contact*, *screenshots*, *Demonstrational Videos*, and *Size*. End users browse through these artifacts before purchasing an app from marketplaces such as Google Play, Amazon Appstore for Android, and the Apple App Store.

App code binary updates are frequent and are typically downloaded and installed automatically unless they require user consent or have been disabled. The app's corresponding artifacts may be updated in the marketplace, but this responsibility of keeping an app's artifacts consistent with each other as well as providing accurate information is distributed across multiple stakeholders, namely developers, users, and marketplace managers.

Our work in this paper requires that we analyze a subset of Android app artifacts to understand and compare what they tell us about how an app behaves. While some of these (rating, description, videos) are straightforward to understand, several others (permissions, Intents) require background in Android app structure, operation, and security features. We summarize some of the fundamental concepts needed to understand our study and results.

An end user downloads and installs an Android *.apk* file from a marketplace, which is actually a zip compression package containing several code artifacts needed to install and execute the app. Of interest to us are the *Classes.dex* file, *res/* folder, and *AndroidManifest.xml* file.

- *Classes.dex* is a java byte code file in Dalvik executable format, generated after compilation from java source, and used by the Dalvik virtual machine in Android. There are various tools that can disassemble and decompile *.dex* files such as dexdump, dex2jar and apktool. These allow *.dex* files to be viewed on their byte- and source-code levels. For example, we obtain the following decompiled code segment for one app:

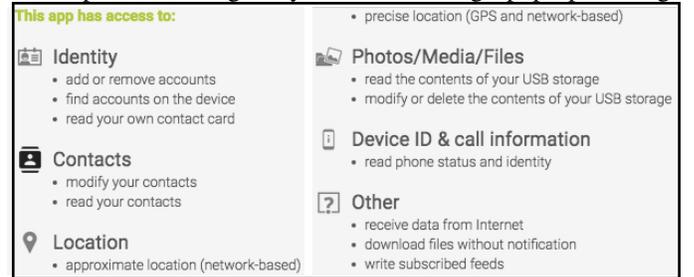
```
# virtual methods
.method public onClick(Landroid/view/View;)V
    .registers 6
    .parameter "v"
    .prologue
    .line 58
    ...
    invoke-virtual {v0,v1,v2,v3},Landroid/hardware/
        Camera;->takePicture(Landroid/hardware/Camera\
        $ShutterCallback;Landroid/hardware/Camera\
        $PictureCallback;Landroid/hardware/Camera\
        $PictureCallback;)V
    .line 59
    return-void
.end method
```

We show the recovered signature of the invocation of *Camera.takePicture()* and its invoking *onClick()* method. Such information may be mined to determine the resources (e.g., the *Camera API*) used by an app.

- The *res/* folder contains all the resources: an image resource, layout resources, launcher icons, and string resources. All this information may be used to better understand the app, e.g., by reading its strings, and examining its icons and GUI widgets.
- The *AndroidManifest.xml* file presents essential information about the app to the Android system. Of importance to us is it declares the permissions the app must have in order to access protected parts of the API and interact with other applications. For example, to take a picture, using the aforementioned *Camera.takePicture()* method, the app needs to declare the following permission in its *AndroidManifest.xml* file:

```
<uses-permission android:name="android.permission.
    CAMERA"/>
```

Such permissions are used by Google Play to inform end users about an app's access to resources and its capabilities, e.g., by the following pop-up dialog:



As discussed above, an app may use cameras on Android devices by invoking the *Camera API* and adding a *uses-*

*permission* block in the `AndroidManifest.xml` file. An alternative way is using the camera via an *Intent* (for our purpose, an *Intent* is an inter-app message) to invoke an existing Android camera app. A camera intent makes a request to capture a picture or video clip through an existing camera app. The app using the *Intent* mechanism does not need to request permission in the `AndroidManifest.xml` file. The developer simply has to create an *Intent* object that requests an image or video, set a resulting image/video file location, and to “send” the *Intent*, using code much like the following:

```
// create Intent to take a picture and return
// control to the calling application
Intent intent = new Intent(MediaStore.
    ACTION_IMAGE_CAPTURE);
// create a file to save the image
fileUri = getOutputMediaFileUri(MEDIA_TYPE_IMAGE);
// set the image file name
intent.putExtra(MediaStore.EXTRA_OUTPUT, fileUri);
// start the image capture Intent
startActivityForResult(intent,
    CAPTURE_IMAGE_ACTIVITY_REQUEST_CODE);
```

After the *Intent* starts, the Camera app user interface appears on the device screen and the user can take a picture or video. When the user finishes taking a picture or video (or cancels the operation), the system returns control to the calling app.

#### A. Related Work

Several researchers have started to analyze various app artifacts with focus on security, quality and reliability. Qu et al. [39] examine the app’s *Description* and *Permission* requests. Their analysis tries to determine whether text in the app description provides any indication for why the app needs a specific permission (they considered only 3 permissions: `READ_CONTACTS`, `READ_CALENDAR`, and `RECORD_AUDIO`). They selected from the top 500 apps specifically for each of the 3 permissions of interest, and analyzed each description with respect to only one permission for which the app was selected. In later work [40], they check for consistency between *Description* and *Permissions*, which they call description-to-permission fidelity. Their results show that the description-to-permissions fidelity is generally low on Google Play with only 9.1% of applications having permissions that can all be inferred from the descriptions. They hypothesize that new or individual developers—those not from a software company—may fail to completely discuss the need for some permission in the app description.

Gorla et al. [35] make use of app *Description* and *API usage*. Their goal is to identify suspicious/outlier apps in respect to API usage. They first examine the description text to cluster descriptions into topics, and then use API calls to reclassify apps as normal or abnormal depending on whether their API usage falls in “normal” behavior, where normal is defined by other apps in the cluster. They mention several weaknesses with the app artifacts in their dataset: code dominated with advertisement frameworks because they used free apps; use of certain words in the description text led to misclassification; analysis of code artifacts may be incomplete

because of their inability to follow *reflective* calls and recover source code from obfuscated binaries.

Chia et al. [14] examine *User Ratings*, *Description*, and *Permissions* to determine that the current forms of community ratings used in app markets today are not reliable indicators of privacy risks of an app. Their large-scale study provided evidence indicating attempts to mislead or entice users into granting permissions. In terms of app artifacts, they conclude that popular and free apps request more permissions than they need. Hence, studies that rely only on such apps may unknowingly skew their analysis of permissions.

The work by Dini et al. [34] uses the largest variety of app artifacts to evaluate app “trust.” They label an app as trusted, untrusted, or deceptive, based on a weighted formula that takes *Developer Rating*, *Number of Downloads*, *Market Name*, *User Rating*, *Number of Crashes*, and *Battery Consumption*. Because of their focus on trust, they ignore app functionality, and consequently code artifacts. Their weighted function gives high weightage to *Developer Rating* (to reward historically trusted developers), with the result that poor quality apps by a trusted developer may be ranked as trusted.

Other researchers have examined only code artifacts to assess security and trust. Huang et al. [33] compare text strings used in the user interface of an app with API calls to determine whether the API usage is consistent with user expectation. We have learned that developers may not always use the `.xml` files, and instead, choose to hardcode the strings into the Java source code, or use images for buttons. Moreover, they may not use all the strings in the `.xml` files.

Fuchs et al. [41] extract security specifications from manifests that accompany such applications, and check whether data flows through those applications are consistent with the specifications. Linares-Vásquez et al. [42] analyze how the fault- and change-proneness of APIs used by 7,097 (free) Android apps relates to its lack of success. They used the apps’ average ratings as a measure of app success; the number of bug fixes in a particular version as a measure of fault proneness; and the number of code changes at method level in a particular version as a measure of fault proneness.

Barrera et al. [43] analyze the Android permission model to investigate how it is used in practice and to determine its strengths and weaknesses, and usage patterns by apps. Peng et al. [44] use probabilistic models to assign each app a risk score based on its requested permissions.

Finally, some researchers have used non-code and non-developer artifacts to assess quality. Galvis et al. [45] process user comments to extract the main topics mentioned as well as some sentences representative of those topics. This information can be useful for requirements engineers to revise the requirements for next releases. Results show that the automatically extracted topics match the manually extracted ones, while also significantly decreasing the manual effort. Fu et al. [46] identify users major concerns and preferences of different types of apps through user ratings and comments. Malmi [47] show how the quality of an app, as reflected in how people start to use it, is linked to the popularity of the

app. They also show the connection between app popularity and the past popularity of other apps from the same publisher and find a small correlation between the two.

Although much of the work on understanding app artifacts is new, there is related work on the topic of general program understanding using reverse engineering [48], which identifies software artifacts in the subject system, and then aggregates these artifacts to form more abstract architectural models [49]. Some of this work has also been applied to specific domains such as the web [50] and service-oriented software [51] that are constantly expanding from simple systems (simple websites and message passing) toward the construction of full-fledged applications. A richer set of artifacts is available when understanding code by programmers for maintenance and evolution of large-scale code [52]. As end users provide online feedback (in the form of accessible reviews), these have also been mined and summarized [53]. Our own recent work on understanding GUI behaviors from test execution [54], [55] is rooted in test case repair and combinatorial coverage [56].

In this paper we attempt to complement prior work by providing an in-depth study that is conducted from a more holistic view. We aim to identify the pieces of the puzzle that contribute to an apps overall specification.

### III. STUDY

In this study we ask three research questions that aim to find out what types of information are required to piece together an app’s true specification. Our first question looks at the descriptive artifacts provided by the developer. The second question examines artifacts that provide indirect information. Our last research question evaluates information provided by stakeholders besides the developer. The questions are:

**RQ1: Which artifacts provide descriptive information of an app’s behavior and are these consistent across artifacts?**

**RQ2: What information can be inferred indirectly from other artifacts?**

**RQ3: What type of specification information and app behaviors are not controlled by the developer?**

#### A. Selecting the Apps

We performed in-depth manual analysis on 14 free apps selected from the Google Play Store. We chose apps that span categories and size (as determined by apk size). Table I shows our sample in more detail. The apps sizes range from 806KB to 49MB and are distributed across 10 different categories. We only selected apps which were expected to be of average to high quality. Such app’s we assumed would be better documented and contain more consistent artifacts. Both of these properties should facilitate our goal of spec construction. The ratings range from 3.6 to 4.6 on a 5.0 rating scale and include several developers with Top Developer badges.<sup>1</sup>

TABLE I: Apps in Case Study

App Name	Category	Developer Rating	APK Size	
			listed	actual
HealthTap (HT)	Health/Fitness	Top	47M	49.5M
Android Auto (AA)	Transportation	Top	27M	27.9M
Nest (NST)	Lifestyle	Standard	24M	25.3M
Kids Puzzle: Vehicles (KPV)	Educational	Standard	21M	20.7M
Peel Smart Remote (PSR)	Entertainment	Standard	17M	17.5M
Diabetes Logbook by mySugr (DL)	Medical	Standard	14M	14.9M
Timely Alarm Clock (TAC)	Lifestyle	Top	9.4M	9.9M
HiFont - Cool Font Text Free (HF)	Personalization	Standard	6.1M	6.4M
Paint for Kids (PFK)	Casual	Standard	6.8M	6.3M
Water Your Body (WB)	Health/Fitness	Standard	5.7M	6M
Spell Checker - Spelling boost (SP)	Books/Reference	Standard	2.9M	3M
IDO Calculators Plus Free (ICP)	Tools	Standard	2.7M	2.7M
Pedometer (PED)	Health/Fitness	Standard	1.9M	2M
Barcode Scanner (BS)	Shopping	Standard	Varies 806K	

#### B. Preparing the Apps for Evaluation

To prepare the apps for manual evaluation, we began by collecting information from each app’s Google Play Store page as well as downloading the respective .apk file. We then performed the following:

(1) From each app’s Play Store page, we scraped the page for developer rating, user rating, user comments, number of installs, screenshots, video (if uploaded), permission request text, listed interactive elements text, whether the app contained in-app purchases, and the text in the app’s description.

(2) From each app’s .apk file, we obtained source code files by disassembling the .apk file into *smali* byte code files with apktool [57]. We also decompiled the .apk file with dex2jar [58] to obtain the app’s Java source code files.

This resulted in a collection of quantitative, categorical, text, and image based information on the app that guided the evaluations discussed in Section IV-D.

#### C. Evaluation Methods

Additional preparation was required for each app’s text, video and image-based artifacts. This included parsing the app’s Manifest file for permission and library usage, parsing code files for API calls and Intents, as well as manual analysis. Manual analysis required the evaluator to watch a video, read text or view a collection of images. After viewing, reading or watching, the evaluator then produced a set of behaviors that the non-code related video, text, or images described. Behaviors were defined as a higher-level action the app could perform that required permission. To address ambiguity within the artifacts and implementation, we listed all possible related behaviors. For example, a description may list “Share with friends” as a feature. This would result in messaging and social media behaviors. Images often contain many behaviors in a single image. For example, suppose a screenshot shows the device with a map and consequently shows the UI which contains a download and sync button. Such a screenshot would result in maps, navigation, download, sync, location behaviors. The reason for including these clusters was to ensure that the inconsistencies found were less a matter of evaluator opinion.

<sup>1</sup>Study artifacts can be found at: <http://www.cs.umd.edu/~atif/puzzle/>

To determine incompleteness of descriptions against permissions, we took each description’s set of behaviors and converted them into the permissions they require. We then went through the app’s requested permissions. First, we looked to see if the permission was accounted for in the desc’s set. If there was a permission unaccounted for in the description that was requested by the app then the descriptions was marked incomplete. If all permissions were accounted for by the description, we then evaluated the app’s behavior on a higher level by comparing its higher level features with its screenshots, videos and our own use of the app. If the app’s behaviors contained in the description were in the app when we used it, we called this app description complete. If there were features in the description not in the app, it was labeled contradictory. The only app we could not use (due to compatibility issues) was *Android Auto*, but the app was already inconsistent and did not require such analysis.

In order to determine each app’s use of advertisement (ad) and analytic libraries, we evaluated the app’s source code files. Specifically, an app was said to use ads and analytics if their disassembled code contained both of the following: (1) the app contained a key for the package in its Android Manifest file and (2) the library’s code was included in the app’s disassembled byte code. We then obtained each of the library’s use of sensitive methods by string searching through the app’s code for API calls found by PScout [59], a tool that extracts the permission specification from the app source code using static analysis, for each app’s Android build and parsing the results for the identified library-related class paths.

To evaluate an app’s use of non-permission protected Intents, we consulted Android documentation. Android lists common Intents and describes several which do not require permissions. While there are many Intents, we focused our studies on those related to otherwise permission-sensitive behaviors—specifically those related to SMS, contacts, internet, phone, calendar and camera/video—in order to see where permissions were lacking information about program behavior. We did not account for those that open a user’s settings although the addition of these could only keep or enhance the findings we present.

In order to evaluate user comments, we obtained the first 20 comments on the app’s Play Store page ranked by newest to oldest and filtered for all versions. This is in contrast to filtering the comments for those only on the latest versions – another option provided by the Play Store. The resulting comments were then combined with the first 20 returned comments ranked from most helpful to least helpful on any version of the app. Helpfulness is determined by fellow users who can rate the comments on the page. Duplicate comments were removed and the resulting set consisted of both most recent ratings as well as those that have been voted as providing the most useful information about the app’s functionality. When evaluating the comments, a comment was considered negative if it indicated either a functionality problem or an indication that the app should undergo changes. This included comments reporting crashes, bugs, freezing, hanging, missing features, and ads.

#### D. Threats to Validity

This study has some potential threats to validity that we outline here.

**Threats to External Validity.** First with respect to external validity, we used only 14 apps and we do not span all categories (we cover 10 of 26). We also do not evaluate only the highest rated apps such as those with 4.6 or above, but instead chose to use a variety of ratings. Given that this is meant as a case study and we are not necessarily generalizing, we believe that this is valid.

**Threats to Internal Validity.** With respect to internal validity, the behaviors we extract may be subjective and require extensive background knowledge of Android’s API and framework. Consistency and incompleteness suffer from the same problem. We erred on the side of caution and always gave the benefit of doubt for consistency when a case was too close to determine. This means that our results should be conservative.

Another internal threat is that the manual analysis was performed by one of the authors of this paper. The manual work might also be subject to mistakes, but we double checked our results to improve our confidence in their correctness. To reduce both of the previous threats we are providing our artifacts and data on our study website.

Another internal threat is that the use of the apps and their documentation were limited to the free portion of the application (features or descriptions that are provided with the paid version are missed). Since we compared artifacts all within the free domain, we believe our results are at least consistent. Additionally, some apps described pro and paid versions on these pages as well as free in their descriptions. Further, each artifact is subject to threats to validity associated with human actions (e.g. any errors the user may have made when filling out the forms). These may contribute to the study’s observed contradictions and inconsistencies. Finally, one app, *Android Auto*, could not be used manually due to compatibility issues, therefore for that app we were restricted to static analysis.

**Threats to Construct Validity.** With respect to construct validity, we could have chosen different artifacts or measures, but we based our analysis on other types of studies that have been performed before on Android.

## IV. RESULTS

We now look at the results for each of our three research questions. We then discuss some observations in more detail and summarize what we have learned from this study.

### A. RQ1: Descriptive Artifacts

To answer RQ1 we examined the data that developers explicitly provide on the Google Play store. When a developer publishes their app on the Google Play Store they are required to give a description with a 4000 character limit. This description then appears on the app’s Play Store page, which in turn can be seen by users to help them determine whether or not to install the app.

As we read each of the apps descriptions, we noticed our apps’ developers were using this space in different ways. Not only were there varying lengths ranging from as few as 57 words to 622 words, but there were differing uses of the descriptions. Some developers were explicitly stating the app’s use of permissions (or providing a link to a site which did so), many others included a bulleted list of the app’s features, while others focused less on its complete behavior, and instead focused on it’s benefits, how it could be used (in a generic way), or just quoted positive reviews.

Table II divides our apps’ descriptions by the type and amount of information present in the description. The first column (len) shows the variation in user description length. The second (Exp) shows whether the permissions were explicit or contained in a link, and the third (List) whether a list of features was provided. In addition, Table II shows whether the description provides extra (non-behavioral) information (Other) such as the benefits of downloading the app. This text does not provide specifications and may actually hurt an NLP analysis. Finally, we show whether descriptions offered incomplete or contradictory information with respect to the app’s actual behavior.

As can be seen from Table II, 7 of the 14 apps had incomplete descriptions and one contained a contradictory statement. The contradictory statement in *IDO Calculator Plus*’s description said that the app did not contain ads when in fact it did. Interestingly, the apps which listed features and stated the permissions explicitly weren’t necessarily immune from being incomplete.

During our evaluations, we noticed that other artifacts on the app’s Play Store page disclosed behaviors that the descriptions had excluded, and as a result, realized that looking at the description alone may be too limited of a scope. Specifically, *developers were using assets such as videos, screenshots and the What’s New section to provide relevant spec information not present in the description.* The most blatant example of this was in Google’s *Android Auto*. The description contains only 57 words and states the app “brings familiar apps and services to a car”. However, it provides a video which demos the app’s use, and screenshots which shows the app’s UI and core capabilities. This shows the user the UI as well as functionalities like the use of maps and navigation, SMS, phones calls, voice commands and scheduling reminders and events. Further, in the app’s *What’s New* section, it includes 74 words explaining the features (16 more words than its description). The new features listed included all of the behaviors shown in the video and screenshots, which were missing from its description (navigation, SMS sending, scheduling & notifications, phone calls, and voice commands). Therefore, while *Android Auto*’s description provided little information on the app’s behavior, other accessible information on the app’s page could impact their expectations. One thing that we noticed is that some of the videos and other artifacts were in languages other than English, which will complicate an analysis.

The apps we studied used on average 9.9 screenshots and nearly half of them included a video that was on average 2

TABLE II: Description Lengths & Usage. ”I” are incomplete descriptions. ”C” are contradictory descriptions.

App	Len	Exp.	List	Other	I	C
AA	57			✓	✓	
BS	184	✓	✓	✓		
DL	243		✓	✓	✓	
HF	197		✓	✓	✓	
HT	622	✓	✓	✓	✓	
ICP	184		✓	✓		✓
KPV	184		✓	✓	✓	
NST	104	✓		✓		
PED	251			✓		
PFK	105		✓	✓	✓	
PSR	317		✓	✓		
SC	197			✓		
TAC	257		✓	✓		
WB	198		✓	✓	✓	
<b>Totals</b>		3(20%)	9(64%)	14(100%)	7(50%)	1(7.14%)

TABLE III: Permission Requests, Intents and API calls.

App	# of Non-permission protected Intents	App	# of Non-permission protected Intents
BS	3	PFK	1
AA	1	SP	1
DL	1	WB	1
HF	1	ICP	0
HT	1	PED	0
KPV	1	PSR	0
NST	1	TAC	0

minutes long. The use of the *What’s New* section varied in our apps. Some developers simply listed ”fixed bugs”, while others offered long explanations of new features like *Android Auto*. Most importantly, we identified approximately 8 behaviors that were not included in the apps’ descriptions that were contained in the videos and screenshots. In summary, nearly half of our apps’ descriptions did not exhaustively and explicitly explain their app’s behavior, and we identified alternative artifacts within an app’s Play Store page where developers disclose spec related information on the app’s behavior.

**Summary of RQ1:** *Play Store app descriptions are used in varying ways. Most of the apps studied had incomplete descriptions and one had contradictory information. Some developers opt to use alternative assets like images, videos, or the What’s New field to reveal additional behavior.*

### B. RQ2: What Types of Inferred Information Exists

To answer this research question we examine types of information that are provided by alternative artifacts (not explicitly provided). For this we use the *AndroidManifest.xml* file and the user interface (UI) itself. We begin with the manifest file. Since prior studies show that the manifest file often over requests permissions, we were surprised to find several cases where the opposite was true, and the permissions lacked important information on the app’s behavior. Specifically, we observed apps that were using Intents to perform significant actions without the need to request permission. These Intents are not those defined in the manifest file, but could be found

by searching the app's decompiled java files. We provide some examples here.

**Paint for Kids.** *Paint for Kids* is a kid's app that provides pages for children to color. It has a user rating of 3.6 and approximately 1,000,000-5,000,000 installations. Its description says it can color, save and share pictures as well as take pictures which can be turned into coloring pages for use in the app. The Play Store page contains a video which demos the app and shows the app taking a picture and then turning it into a coloring page. Screenshots show painted pictures as well as buttons with icons for saving, sharing, painting and taking pictures. Despite all indications of camera usage, however, when a user asks to install the app, no camera permission is requested and no permission request appears in the app's manifest file. When the app is used, the camera is indeed opened by the camera button, and everything else proceeds as demoed in the developer's video.

What allows *Paint for Kids* to use the camera without a user's permission is that the app is invoking the camera via a non-permission protected Intent. This Intent allows the app to employ another app on the device to take and save the picture. *Paint for Kids* then has access to the saved image and can do what it likes with the file. Intents exist for other typically sensitive operations such as creating and writing SMS texts, editing contacts, dialing phone numbers and capturing video [60]. An app (possibly malicious) may circumvent the permissions by accessing these sensitive operations via Intents.

Table III shows the number of such Intents not accounted for by an app's permission list, along with the number of permissions the app does request. 10 of the 14 apps used this mechanism to access protected resources. Surprisingly, *Paint for Kids* was not the only app aimed at children with such behavior. *Kid Puzzle-Vehicles* included an ad-related class that dialed phone numbers. Although the phone itself is not invoked, the dial pad will pop up with a number, and a child can then easily press the call button to execute the call.

The second artifact we used for inference was the UI since it offers additional information about what an application does and impacts the user's expectation. For example, a user might see an icon of an envelope and will expect the app to be associated with some sort of messaging or email behavior. Several studies have identified the UI as a source of valuable information for program understanding [33], but most evaluate the app's strings statically and leave the icons as future work. As a result we were interested in evaluating how an app's strings and icons interact with respect to what unique information they each provide. In short, do our app's icons provide information that is not available in the app's strings?

To answer this question, we manually evaluated all of the app's strings defined in values and values-en as well as all included .png files in drawables, drawables-nopi and drawables-hdpi that were icons (i.e., not images or graphics used for content or background purposes) and listed the associated behaviors for each string and icon. Because app's often include the same icon for different states (such as pressed and active), the unique images within the drawables was typically much

less than the number of included .png files. During our analysis we failed to find a icon-related .png that did not contain a defined string that defined it. That said, the set of defined strings in our apps greatly outnumbered the defined icons so this may be a superset of information.

In summary, the collective set of icon-related .pngs in drawables, drawables-nopi, and drawables-hddpi was contained in the combined set of strings in values and values-en. What remains unclear and may be a subject for future work is either set's relationship to our app's actual UI and behavior—whether the icons are a more concise representation of the UI or whether the strings define too many false values not used by the app.

**Summary of RQ2.** *We conclude additional (and possibly differing) information for an app's spec is indirectly available through the permission set, non-permission protected Intents, and/or the app's UI as represented by sets of icons and strings. Our research suggests that the icons an app defines have significant overlap with its strings.*

**C. RQ3: What Externally Controlled Information is Available?**

To answer the last research question, we turn to three pieces of information that are not explicitly provided by the developer – advertisements, user ratings and user comments.

**Advertisements.** Little information on advertisements (ads), analytics and social media libraries was contained on the app's Play Store page, yet these libraries present obstacles in specification construction at the code level. First, they introduce extra code in the source code files, icons, and strings which may potentially cause a specification to include behaviors an app doesn't actually perform. Second, they often employ reflection causing an app's API calls to be incomplete [38], and as confirmed in our case studies, little information about them can be obtained from the Play Store – apps tend not to be upfront about their usage. Last, they can be dynamically added and removed (e.g., the app might cycle through or change their advertisers on a regular basis, and the ads themselves, may evolve on a cycle that differs from the app evolution). In fact, some other studies have chosen to remove ads from their analyses [37], [38]. Since our case studies were all free apps, the use of ads, analytics and social media service libraries may not be surprising. We observed on average 2 such libraries in each app with one app containing as many as 5 and another not containing any. It is relatively easy to determine if an app includes a library based on the source code, but it is difficult to determine what aspects it uses due to the presence of dead code and use of reflection. Two cases that we present next help us show some behaviors found in our app's code that appeared related to the libraries.

**Kids Puzzle - Vehicles.** *Kids Puzzle - Vehicles* is a children's game app that also teaches the user different languages. Its description describes the different levels and characters of the game as well as the benefits of learning a new language. Its Play Store page confirms these behaviors and includes screenshots of the different games children can play as well

as different languages to use while playing. It has over 50,000 downloads and a user rating of 3.9. Five of the 28 comments evaluated reported the app hanging, crashing, or freezing and one of these comments reported crashing because of ads. This comment was the only mention of ads on the page. The app requested 12 permissions and included several which were not described by its description, UI or comments. These included READ\_LOGS and MOUNT\_UNMOUNT\_FILESYSTEM. While evaluating the byte code further, we found that the app included the Umeng ad library, which has been reported as harmful adware [61]. No mention of Umeng were in the description and the app did not include an interactive elements section. Umeng could be detected when inspecting the resource files for the app. Execution of the app also revealed ads, which were not mentioned in the app description.

**HealthTap.** *HealthTap* is a health related app that allows a user to search and consult with doctors via text, video and phone as well as send them medical documents and images. Its developed by a Top Developer, has 1,000,000-5,000,000 installs and a rating of 4.4. It requests 22 permissions including those related to location, camera, recording audio, accounts, contacts, and internet. While their app requires a lot of permissions, each of these could be reasoned from the description, which is over 600 words long. In the description, videos and screenshots, no mention of ads or social media services appears, however they were included in the app's code and were in the UI pics and strings as well as the Android Manifest file where their keys and meta data were included. When viewing the page, a viewer may infer the app used location to personalize feeds as well as facilitate other features like searching for doctors and prescription delivery, which were features of the app. The byte code indicated other undisclosed uses such as tracking the user to send localized marketing via push notifications.

In summary, we saw that apps only occasionally mention ad libraries to users in the app's descriptions, never disclosed the use of analytics, and never showed ads or analytics in screenshots or videos. Furthermore, when ads were mentioned they were typically inferred when the description mentioned that the paid version contained no ads or in user comments complaining about them. The store's new interactive elements category [62] (described in Table V) may help with this, although it is still new and not all developer's have updated their pages to include this information. For the purposes of constructing the app's specification, this category will not solve all the presented issues. These two examples help demonstrate that while the use of ad and analytics libraries may be expected in free apps, their specific behaviors are important to include.

**User Provided Information.** Every app's Google Play Store page contains several user-controlled categories that display information submitted or defined by the app's users. These categories include developer ratings, number of installs, user comments and user ratings. We included these artifacts in our evaluation to assess what information they could provide and

to determine whether they could be used as indicators of the app's general quality.

Table IV presents these artifacts and other measures of quality for each app in our study. We were surprised to see the apps that had reports of major functionality issues— such as reported crashes, freezing, and buttons not working— continued to be downloaded by many users and receive high user ratings. Two examples are discussed next.

**Peel Smart Remote.** *Peel Smart Remote* is a remote control which enables a user's Android device to control his or her television, Apple TV, etc. The app's description explains that *Peel* can personalize viewing, set reminders and change and customize channels. When evaluated against the app's permissions, the artifacts appeared relatively consistent. Despite its overall consistency, user comments suggest the app may functionally be sub-optimal. At the time of the study, 3 out of it's then 20 latest reviews report crashing and 4 additional comments reported freezing and dysfunctional button usage. Despite these complaints, the app holds a 4.4 rating on a 5.0 scale.

**Timely Alarm Clock.** *Timely Alarm Clock* is an app that allows you to synchronize alarms across multiple devices. Its description describes the app's ability to sync devices and customizable interface, and its UI is straightforward with clock-related icons and strings. Its video highlights the app's customizable UI and alarms as well as its ability to sync with devices, work as a timer, and adjust audio with different user gestures. Like *Peel*, *Timely Alarm Clock* received many complaints. Seven of the last 20 comments at the time of the study reported functionality issues such as not being able to turn off the alarm, the set alarm not going off or going off late, and its time lagging behind the system clock. In the combined set of helpful and new user comments spanning all versions, 25 out of 40 were negative. Nonetheless, *Timely* maintains a very high user rating of 4.4 as well as a Top Developer badge.

Such contradictions were witnessed in several other apps as well. Table IV lists the apps by decreasing percentage of negative comments received. Apps with 5 million downloads and user ratings of 4.4 received a high percentage of negative comments. Furthermore, as indicated by the location of the check marks in the table, developers with Top Developer badges appeared to receive just as many negative comments as non-top developers, with some receiving as many as 60-70% negative comments. Such results suggests that either user ratings and developer ratings were not indicators of quality in our study or perhaps the sample of user comments were biased towards negative reviews.

We did identify one potential reason for this discrepancy, which might help explain *Peel Smart Remote*. User ratings are cumulative and include ratings from older versions of the application, while user comments can be sorted by decreasing variables (such as date, helpfulness and rating) and filtered by the latest or by all versions. When evaluating the different filters, the returned results tended to favor more recently submitted comments even when sorted by helpfulness. As a result, for some apps, this inconsistency between ratings and

TABLE IV: Negative Comments, User Ratings & Quality. "TD" indicates whether the app was developed by a Top Developer. "DR" is whether the number of times the developer responded to negative comments. "CR" is the number of comments that indicated crashing or freezing. "LH" is whether the app had the `<:largeHeap>` attribute set to true. This determines whether the app's processes are created with a large Dalvik heap and is discouraged by Android.

App	Installs	TD	User Rating	Size	Neg. Comments	Repeating Issues	DR	CR	Perm	Lib	LH
AA	>10K	✓	3.7	27M	28:38 (73.6%)	Compatibility, Night Mode Needed, Car Display Requirements, Limited App Support	0	1	16	0	
PSR	>10M		4.2	17.5M	20:29 (68.9%)	Crashes, Issues w/ Update, no guide available, button functionality issues	1	3	13	0	
NST	>500K		4.4	25.3M	25:38 (65.7%)	Offline, Auto-Sched. & Geofencing Doesn't Work	0	1	12	2	
TAC	>5M	✓	4.4	9.9M	25:40 (62.5%)	Can't Dismiss Alarm, Alarm Doesn't Go Off When Phone is Silenced, Dislike of Notifications for Upcoming Alarms, Requests for Skip Next Features, Wrong Time	0	1	14	1	
BS	>100M		4.1	806K	21:40 (52.5%)	Slow to Scan, Won't Scan	2	0	9	0	
SC	>1M		3.9	3M	16:32 (50%)	Ads, Crashes, Trouble w/ Foreign Languages, Doesn't Work, Char. Limit	1	3	4	4	
HT	>1M	✓	4.4	47M	12:29 (41.3%)	Wrongly Charged For Services, Freezing	8	2	22	2	✓
PFK	>1M		3.6	6.4M	11:27 (40.7%)	Ads, Slow to Download	0	1	4	1	✓
DL	>1K		4.6	14.9M	10:38 (26.3%)	Include Carb Search, Too Expensive to Upgrade	1	0	14	2	✓
PED	>1M		4.2	2M	9:38 (23.6%)	Inaccurate Step Counting, Trouble Resetting Session	0	0	4	2	
KPV	>100K		3.9	20.7M	5:28 (17.8%)		0	3	12	2	
HF	>10M		4.2	6.4M	7:40 (17.5%)	Trouble Installing Fonts	0	0	19	5	
ICP	>500K		4.1	2.7M	4:29 (13.7%)	Permanent Ads in Notification Bar	0	0	10	2	
WB	>5M		4.5	6M	4:37 (10.8%)	Ads		0	11	1	

comments may be explained by a high user rating reflecting a history of high-quality and negative comments which may reflect a poor release or update. In essence we are comparing data from different points in time and this could be problematic for a user.

In conclusion, we saw inconsistencies between user approval indicators such as user ratings and installs and app quality indicators such as developer ratings and user comments. We also saw inconsistency between developer ratings and user comments. These may be explained by the user approval being unrelated to quality, or the user comments containing a bias in either how they are ranked and displayed by the Play Store, or how users use them (such as dissatisfied users are more likely to submit a comment than satisfied users). Either way, the app's within our study with high user ratings or a Top Developer badge did not appear to indicate that the latest version available on the store was not buggy.

**Summary of RQ3.** *We see that there is dynamically added behavior (in the form of ads) that should be accounted for if we want to understand an app's true behavior. This is usually not discussed by the developer and may not be known. We also see that user approval and quality measures such as number of downloads, user & developer ratings and user comments can be utilized, but they were contradictory. Such contradictions may be a result of versioning or suggest that comments and ratings can not be compared.*

#### D. Summary Discussion

We now synthesize what we have learned from this study. Table V shows a summary of the artifacts we have studied

in this paper. For each it shows whether they are located on the Play Store or in an apk file, their visibility to the user, what information they contain, whether they provide behavioral information, and an overview of their potential source of inaccuracy when assembling an app's specification. Together these pieces should be combined to understand true specifications. As can be seen, many new analyses are needed to extract and merge this information. Our key findings are: (1) The apps' developers use descriptions in varying ways and other artifacts on the webpage, such as screenshots and videos, are also being used for specification purposes. We saw that some may be presented in differing languages (e.g. the app *Paint for Kids* has its app description in English but the demonstrational video language is Portuguese). Such results suggest that an app's description alone is not an accurate representation of either program behavior or user expectation of a program's behavior, and that alternative analyses that can extract information from artifacts such as video or screenshots is needed. To get a full specification, these analyses should ultimately be merged.

(2) While it is known that apps over-request permissions and therefore permissions may contain behavioral capabilities not actually utilized by the app, we saw several apps whose permission sets lacked information regarding important behaviors the apps perform. This offers yet another reason why permissions alone cannot be used as an app's specification.

(3) The majority of apps in our study contain ads and analytic libraries. Under the current developer practices such libraries present obstacles in program understanding. Specifically, they

TABLE V: Synthesized Android Artifacts Used in our Study. In the column "Creator", "D" is for developer, "U" users, and "M" the Google Play Store market. In the column "Type", "N" is for numerical, "C" categorical, "T" textual, and "P" pictorial.

Artifact	Creator	Type	Potential Information	Behavioral	Source of Inaccuracy	Previous Work	
Google Play Store (visible to user)	Description	D	T	App features and behaviors.	✓	May be incomplete. Developers could use other elements of the page instead.	[35, 36, 39, 40]
	What's New	D	T	Features added to the latest updates.	✓	May be incomplete. Developers could use other elements of the page instead. May only include changes, not overall app behavior.	
	Screenshots	D	P	Visualization of app behavior and design.	✓	May be for an older version. May be absent from the page.	
	Videos	D	P	Real-time behaviors and design.	✓	May be for an older version. May be absent from the page.	
	Interactive Elements	D	C	Whether the app does the following: shares personal information with third-parties, shares location, allows purchases, contains user-provided uncensored content and/or has unrestricted internet access.	✓	May not be included by developer.	
	User Comments	U	T	Functionality, user approval, and behaviors	✓	May include previous versions. May be device specific.	[25, 26, 27, 45, 46, 53]
	User Ratings	U	N	User approval and quality.		May not reflect the latest version.	[34, 42, 46]
	Developer Rating	M	C	An indicator of developer trust and app quality.		May not reflect the Developer's latest version or project.	[34]
	Installs	U	N	The number of times the app has been downloaded by users.		Does not reflect number of uninstalls after install.	[34]
	Permissions (as listed on the Play Store)	D	C	The sensitive operations an app can perform.	✓	Displays certain categories of permissions only, so list may not be an exhaustive. May include permissions not used by the app. May miss behaviors performed via non-protected intents.	[14, 29, 31, 33, 35, 36, 37, 39, 40, 43, 44, 59]
.apk file	Strings (in strings.xml)	D	T	Text that may appear in an app's UI.	✓	May not be used at runtime. May be an incomplete set because of hardcoding.	[33,36]
	Images (in /res/drawables)	D	P	Images that may appear in the app's UI.	✓	May not be used at runtime.	
	Permissions (in Android Manifest file)	D	C	The sensitive operations an app can perform.	✓	May include permissions not used by the app. May miss behaviors performed via non-protected intents.	[14, 29, 31, 33, 35, 36, 37, 39, 40, 43, 44, 59]
	Bytecode API calls	D	T	Android library calls.	✓	May contain dead code, include ads which use reflection, obfuscation, excludes method arguments values that are obtained at runtime.	[35, 36, 37, 38, 42, 43]
	Source Code API calls	D	T	Android library calls.	✓	May contain dead code, include ads which use reflection, obfuscation, excludes method arguments values that are obtained at runtime.	
	<meta-data> &lt;br><uses-library> elements	D	T	Libraries included.	✓	May be dead code.	[38]

complicate the use of API calls through their use of reflection and injection of large amounts of dead code. Little information about their behavior is available on an app's Play Store page other than the mention of their absence in paid versions and user comments mentioning related crashes, freezing and general annoyance. No mention is ever made about analytics.

(4) While the number of downloads, user ratings and user comments may seem like similar measures of user approval and even program quality, we observed contradictory results in several apps where users reported many bugs but users continued to download the app and rate it highly. Within our

study, such negative comments were independent of whether the developer had received a Top Developer badge.

## V. CONCLUSIONS AND FUTURE WORK

In this paper we have tried to identify the puzzle pieces that are required to determine an app's true behavior. We call this a puzzle because, as we have shown, the behavior (or app's specification) is never fully explicitly revealed to an end user in a document. Instead, the behavior is revealed "in pieces" across the multiple artifacts that typically accompany an app. These pieces need to be put together to understand true be-

havior. This is important if we are concerned about evaluating the app's quality or testing it for functional correctness or suspicious behavior.

In our study of Android apps, we have learned that developers do not use descriptions in a consistent manner. In order to fully understand a complete description, one must add visual (screenshot and video) analysis. We also find that artifacts that provided inferred behavior (e.g., AndroidManifest.xml file's permissions section is thought to provide complete knowledge of the app's phone usage such as dialer, camera, and microphone) may not be complete as there are dynamic behaviors from advertisements that are almost completely ignored by developers and poorly documented. Finally, we have learned that user ratings and comments follow an app through its history, therefore newly introduced faulty behavior will not be reflected in ratings.

As future work, we are developing a multi-dimensional analysis that can automate the extraction and merging of these information sources. We also plan to add additional external resources to our analyses, such as the Symantec website that catalogs potentially harmful libraries like Umeng, or those such as Android Central<sup>2</sup> that provides additional reviews of apps, of which this is a quote about Gentle Alarm: "The free version of this app has all the features but there is only one catch. The alarm will not ring on Wednesdays." We confirmed that this exceptional behavior is not mentioned on the Marketplace website. We will then use these new analyses and additional data sources to perform a larger scale case study on more apps.

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