What Aspects of Mobile Ads Do Users Care About?
An Empirical Study of Mobile In-app Ad Reviews

Jiapeng Gui*, Meiyappan Nagappan† and William G. J. Halfond*
*University of Southern California, Los Angeles, California, USA
†University of Waterloo, Waterloo, Ontario, Canada
Email: {jgui, halfond}@usc.edu
Email: mei.nagappan@uwaterloo.ca

Abstract—In the mobile app ecosystem, developers receive ad revenue by placing ads in their apps and releasing them for free. While there is evidence that users do not like ads, we do not know what are the aspects of ads that users dislike nor if they dislike certain aspects of ads more than others. Therefore, in this paper, we analyzed the different topics of ad related complaints from users. In order to do this, we investigated app reviews that users gave for apps in the app store that were about ads. We manually examined a random sample set of 400 ad reviews to identify ad complaint topics. We found that most ad complaints were about user interface (UI) related topics and three topics were brought up the most often: the frequency with which ads were displayed, the timing of when ads were displayed, and the location of the displayed ads. Our results provide actionable information to software developers regarding the aspects of ads that are most likely to be complained about by users in their reviews.

I. INTRODUCTION

In just a matter of a few years, the global market has experienced a tremendous increase in the number of apps that consumers use on their smartphones. As of June 2016, both the Google Play and Apple app store boasted over two million apps [1]. Along with this growth in apps, mobile advertising in apps has become an important source of revenue for software developers [2]. In 2010, the mobile advertising industry’s revenue was just over half a billion dollars [3]. By 2018, analysts predict that revenue from mobile advertising will reach 160 billion dollars and account for 63% of all global digital advertising spending [4].

In the mobile advertising ecosystem, there are four main stakeholders: end users, developers, advertisers, and mobile ad networks (MANs). To earn ad revenue, developers embed and display ads in their apps. MANs, such as Google Mobile Ads and Apple iAD, facilitate the interaction between developers and advertisers. To do this, MANs maintain and distribute libraries that enable developers to include ads served by the MAN in their apps. When an end user clicks on or views ads, the developer receives a small payment from the MAN on behalf of the advertiser.

An important additional, but somewhat indirect, player in the mobile ad ecosystem is the app store. Users can leave reviews and rate apps in the app store. This feedback can influence the behavior of other users, who may avoid negatively rated apps, and can also be a source of useful bug reports or suggestions for improvement for developers. Prior studies have shown that these reviews cover a wide range of topics, such as the app’s functionality, quality, and performance [5] and that specific areas of complaints, such as user dissatisfaction with ads, can negatively impact the ratings an app receives [6]. It is in the interest of developers to avoid negative reviews and ratings as these will make their app less appealing to new users or cause the app to be ranked lower by the app store. In turn, fewer downloads of the app are likely to lead to fewer ad clicks and views, which cuts into potential advertising revenue that could be earned by developers. However, in the case of ads, the situation is more complicated. Developers will not simply remove ads, but must find a balance in their use of advertising that avoids a negative experience, but still enables them to earn advertising revenue.

The effect of reviews and ratings on developers’ advertising revenue motivates them to understand what aspects of ads could cause negative experiences. However, developers lack practical and even basic information about which ad-related aspects are more or less likely to produce a negative experience for their users. Although many developer blogs (e.g., [7], [8], [9]) attempt to provide such guidance, and even ad networks often suggest “best practices” (e.g., [10], [11]), this information is often anecdotal, lacks rigorous evidence to support the advice, or is too generic to provide developers with concrete guidance. Furthermore, developers lack a systematic ability to analyze and understand ad related reviews. Although there has been extensive study of app store reviews (e.g., [12], [5], [13]), this work has not focused on ad specific complaints.

To address this issue, we conducted an empirical analysis of ad related reviews. In this paper, we present the results of this investigation, which enabled us to identify many different aspects of ads that frequently trigger ad complaints. To carry out this investigation, we performed a systematic approach as below:

1) We began by identifying ad related complaints from a corpus of over 40 million app store reviews. We found that there were, in fact, a large number of user reviews that discussed mobile advertising.
2) We then analyzed the ratings and text of the reviews and found that those that mentioned advertising were disproportionately likely to receive lower ratings.
3) In a manual analysis, we analyzed a statistically significant sample of these reviews to identify the most
common topics of end user complaints. Our findings were that most complaints were related to how ads interfered or interacted with UI related aspects of the mobile app. In particular, we found that UI issues relating to how frequently the ad was shown, when the ad was displayed, and where the ad was placed were the most frequently mentioned complaints. For non-visual aspects, the behaviors such as the ad automatically downloading files or changing system settings, blocking or crashing the host app’s execution were the most frequently mentioned.

Overall, these results showed clear trends in users’ ad-related complaints that can help developers to better understand the aspects they should be most concerned about when placing ads into their apps. Better understanding of these aspects can improve the overall app user experience while allowing developers to continue to take advantage of the potential mobile ad revenue.

The rest of our paper is organized as follows. In Section II we introduce and motivate each of the research questions we address in this paper. In Section III, we describe the infrastructure and protocol for collecting the ad meta data. Then in Section IV, we describe the details and results of the analysis we carried out for each of the research questions. The threats to the validity of our results are discussed in Section V. Next, in Section VI we discuss the implications of our findings and how these motivate future work in different areas. Finally, we cover related work in Section VII and summarize our findings in Section VIII.

II. RESEARCH QUESTIONS

Our investigation broadly focuses on end users’ app store reviews that relate to mobile advertising. To better understand end users’ reactions to ads, we first focus on identifying how many such reviews exist in the app stores, then we analyze the distribution of ratings associated with these reviews, and finally we identify the ad related topics in the reviews. Below we more formally introduce and motivate our research questions (RQs).

RQ1: How frequent are ad related reviews among all app reviews?

An app store allows users to write textual reviews of the apps they have downloaded. If users have had a negative experience with mobile advertising, they are likely to comment on this in their reviews. Therefore, our first, and most basic, research question examines the frequency of app reviews that include comments on mobile advertising. The results of this RQ can serve to inform developers at to how prevalent such reviews are in the corpus of all reviews. We also are interested in determining if this frequency varies by category. In other words, are certain categories of apps more or less likely to get comments related to ads?

RQ2: What is the distribution of star ratings among ad reviews?

Along with the textual review, the app store also allows users to leave a numeric rating for each app. This is typically provided by a user on a scale of one to five, with five being the highest, and is often referred to as “awarding stars” since the graphical representation of a rating has traditionally been a star for each rating point. Developers care about these ratings because they influence how app stores display apps in response to a user search. Higher rated apps tend to be given more priority when displayed to the user. Therefore, in this research question we are interested in determining the ratings distribution of ad related reviews. We expect that results for this RQ could indicate the type of influence ad related reviews are having on an app’s overall rating.

RQ3: What are the common topics of ad complaint reviews?

Complaints in ad related reviews may be due to numerous reasons. For example, users may be upset when an ad is interfering with the display of important information or appearing too frequently. For developers it is important to understand what aspects of ad usage or behavior is causing user complaints so that they can focus their efforts on these aspects. Therefore, in this research question we are interested in determining the ad complaint topics, that is the specific aspect or issue related to ads that users are complaining about in a review. The results of this RQ would inform developers as to the most problematic aspects of ad usage and guide them in determining how to improve their apps’ ad usage.

III. DATA COLLECTION

In this section, we describe briefly our protocol for obtaining the data that is used to address each research question listed in Section II.

To collect app reviews, we crawled the Google Play app store everyday using a farm of systems for over two years (January 2014 to October 2016), to download every new release (i.e., APK) of the app and its associated meta-data, such as average user rating, user reviews (500 at a time), and their corresponding app ratings, among other things. For the collection, we downloaded the top 400 ranked apps (as ranked by Distimo [13]) in 30 officially recognized app categories that resulted in a corpus of more than 10,000 apps and over 40 million app reviews.

IV. RESULTS AND DISCUSSION

In this section, we discuss the details of the approach we employed to address each of the RQs, present the results we obtained, and discuss the implications of these results with respect to each of the RQs.

A. RQ1: How frequent are ad related reviews among all app reviews?

Approach: To answer this research question, we applied the regular expression (i.e., regex = ad/ads/advert*) to filter out ad related reviews from all of the collected app reviews (see Section III). We chose these particular keyword variations based on guidelines provided in the related work that also manually examined user reviews for different types of user complaints [5]. We then counted the frequency of ad related
reviews and their percentage with respect to all of the reviews. We also calculated similar information for each of the 30 standard app categories.

Results: We obtained in total 529,827 ad related reviews out of over 40 million app reviews. This indicates that approximately 1% of all user reviews dealt with in-app ads. The frequency of ad reviews varies among the 30 app categories. Nine categories have an ad review ratio over 1.5%, and eight have less than 0.8%. As for the absolute numbers, seven have over 30,000 ad related reviews, and one has over 50,000. The median number and ratio of ad reviews per category are 11,669 and 0.96% (comparable to the overall ratio), respectively.

Discussion:

From the results, we can see that ad related reviews are non-negligible. In fact, there are a large amount of such reviews from end users. From this perspective, developers are able to extract useful information about mobile ads to improve the user experience of their apps, since these reviews are the feedback directly from end users. This further motivates us to inspect ad reviews in the following section to determine what ad aspects that users care about and thus matter to developers. Ostensibly, the ratio of ad reviews is too small to cause developers’ attention. Nonetheless, these reviews do have a measurable impact on the ratings, as we demonstrate in the next RQ. Past research has also shown the similar impact that ratings of apps could be affected when they receive poor reviews [6]. Moreover, mobile advertising has become one of the main resources for the revenue developers receive when they publish free apps in the app store. Hence, this ad ratio, albeit with a small percentage, is enough to be worthy of developers’ attention.

We also found that the frequency of ad reviews varied by category. In particular, two app categories, BRAIN and ENTERTAINMENT, were high in both the number and ratio of ad reviews. Another two categories that are worthy to note were COMICS and MEDICAL. They had a high ad review percentage in spite of the relatively small number of ad reviews. This reflects that end users commented on such kinds of apps not as actively as in other app categories, but negative experiences with ads tended to be one of the big problems that would cause users to complain. Such a higher number or ratio in any of the four categories mentioned above could either mean that developers are more aggressively embedding ads in apps of these categories or that users of such apps have a lower tolerance for ads. In either case, developers need to be more cautious to prevent the loss of users and thereby sustained revenue.

B. RQ2: What is the distribution of star ratings among ad reviews?

Approach: To address this research question, we leveraged the same approach as in the previous RQ, but calculated the frequency distribution of both ad and non-ad review ratings.

Results: Table I shows the distribution of all reviews with different rating stars. We can see that, for the ad related reviews, almost half (about 46%) of the reviews are complaints (i.e., have one or two star ratings). In contrast, most of the non-ad reviews have five star ratings with only about 17% being complaints.

Discussion: These results show that reviews mentioning ad related topics are disproportionately more likely to be a complaint than non ad related reviews. Thus these reviews, with their corresponding ad complaint topics, can convey valuable information about what kind of ad aspects developers should address to improve their app ratings. The high ratio of low ratings among ad related reviews also suggests that ad related complaints can have a significant negative impact on app ratings. Intuitively, such results are unsurprising, but do provide motivation to further investigate and understand which aspects of ads developers can address to improve their apps.

One might wonder if since ad reviews together comprise only a little more than 1% of all of the reviews, are they likely to have an impact on ratings that would register with the developer. Consider the case where an app has 1,000 non ad related reviews and 11 ad related reviews, all with four-star ratings. If one of these ad reviews had only a one-star rating, then the app’s overall average rating would drop to 3.997, a decrease of about 0.003 stars. This is a small number, but related work has shown that even such small changes are sufficient to change the rating based ranking of an app [6], which in turn, could cause apps to be displayed in a less favorable position in response to a user search.

C. RQ3: What are the common topics of ad complaint reviews?

Approach:

To answer this research question, we carried out a manual analysis of a large subset of the ad related reviews to determine the most common ad complaint topics. In this study we focused on ad related complaints and not the general topics relating to ads. To identify complaints, we first filtered the corpus of 529,827 ad related reviews to leave only those that had received a rating of two stars or less. Prior studies have shown that these reviews are primarily negative or complaints [15]. Based on the corpus size of 246,370 ad related complaint reviews, we randomly sampled 400 reviews to give us a 95% confidence level with a 5% confidence interval. This sample size ensures a high degree of confidence that our categorization results would be indicative of the larger population.

We then analyzed the 400 reviews to identify the ad related complaint topics. Our analysis involved two phases. The first phase was a high-level classification of whether the review was actually a complaint. Essentially, this allowed us to filter out any reviews from our original set of 400 that were rated

| Table I: Distribution of reviews with respect to their star ratings |
|--------------------------------|---|---|---|---|---|
| Review rating | * | ** | *** | **** | ***** |
| % of Ad related reviews | 33.29 | 13.21 | 14.51 | 17.11 | 21.89 |
| % of Non-ad related reviews | 12.12 | 4.51 | 7.27 | 15.11 | 60.98 |
Results and Discussion:

1) High Level Category Distribution

Our first result is a high-level classification of all 400 ad related reviews. This is shown in Figure 1. In this figure, we report the number of reviews that were not ad complaints (“not complaints”), the number of complaints for which a topic could not be determined (“non-descriptive”), and then a broad categorization of the remaining complaints (“descriptive”). At a high-level, we found that most of the ad reviews with low ratings were indeed complaints about ad aspects. Of the 400 reviews, 95% (descriptive + non descriptive) had complaints, and only 5% (non complaint) were positive or neutral in their comments about the ads.

Among the two categories containing complaints, we found that about 20% were non descriptive. Examples of comments we found in this category were: ‘Ads are annoying’ and ‘Ads suck, suck’. For such reviews, we could not extract useful information related to their topic, except to determine that they were complaints about ads.

Of the remaining descriptive ad complaints, we found that most were topics that could be considered UI related. These focused on visually observable aspects (e.g., size and location) of the ads and how they interacted or interfered with the UI. Altogether, reviews in these complaint topics represented about 66% of all of the reviews and their breakdown is shown in Figure 2a. The non-UI related ad complaint topics dealt with ad functional properties (e.g., a slow down in the app’s execution or unexpected audio). They represented about 10% of all ad reviews and their breakdown is shown in Figure 2b. Note that the sum of the complaint topics in Figure 2 does not equal the 294 as shown in Figure 1 since some reviews contained more than one complaint. We now discuss the specific ad complaint topics that were categorized as UI, non UI during our manual analysis.

2) UI Related Ad Complaint Topics

The distribution of UI related ad complaint topics is shown in Figure 2a. Overall, we found nine distinct UI related complaint topics, each of which is shown in Figure 2a along with their frequency of occurrence in the reviews. Below, we describe the nine topics in more depth and give examples of users’ complaints about each topic.

Interstitial (popup and video): In general, there are two types of ads that can be included in an app by a developer: banner and interstitial. Ads that occupy the full screen are called interstitial ads. Others, that appear as narrow horizontal strips, are typically referred to as banner ads. Interstitial ads generally have a higher payout than banner ads [16]. However, users may react negatively to interstitial ads because they require the user to view the ad for a time interval or click a close button to return to the app. For example, in a review of an app where an interstitial ad popped up and interrupted a user’s interaction with the app, one user complained ‘...Ads pop up full screen. Uninstalled.’. Another user complained ‘Ads have gotten out of control. Auto-play video ads with sound are not cool. Uninstalled.’. This type of review represented 23.7% (62/262) of the total UI related complaints.

Frequency: This topic deals with how often ads appear in an app. Current mobile ad networks pay developers based on the number of ad clicks or ad impressions they achieve in their app. Therefore, developers are incentivized to encourage user clicks and ad views. A developer may believe that one way to achieve this is by displaying more ads in their app. However, users may be annoyed by too many ads, since it could be distracting or unsightly. In the UI related ad reviews that we
analyzed, we found many complaints (44.7%: 117/262) were related to ad frequency. One user wrote ‘Ad overkill, Too many ads’ and another ‘Ads Ads Ads. As soon as I opened it, bang! Hit with an Amazon ad. That’s enough for me, uninstalling now!!’.  

Size: This topic focused on how big an ad is in relation to the app’s UI. To attract the user attention to ads, developers may be tempted to make their ads bigger so they stand out. However, as the ad size becomes larger, it can affect the users’ ability to interact with the app. For example, ‘... ads at the bottom started getting bigger eventually blocking the next level button.’ and ‘Stupid slot. Ads with slots covering the screen! People love casino on mobile but I think it is boring!’ We found that 8.8% (23/262) of the ad UI related complaints were related to the size of the ad.  

Location: This topic includes complaints about where an ad is within the app’s UI. Developers may place ads anywhere in the UIs of their app. Odd positions may increase the attention brought to the ad, which could lead to more clicks. However, ads in certain positions, such as the middle of the page may be disruptive to the usability of the app. For example, one user complained ‘Ads on the middle hate’ and another posted ‘Ads in the way. I can’t read the quotes with the ads in my way. Uninstalled.’. Ad position directly impacts the layout of other elements in the page. For instance, if an ad is displayed in the middle of the screen, other elements can only occupy the upper half and lower half of the page. In some cases, an ad may even overlap with other visible elements. We found that 18.7% (49/262) of the UI related reviews were related to the position of the ad in the screen.  

Notification: Besides displaying relevant content, ads can attract users’ attention by sending an alert or notification to the status bar. However, notifications can also trigger users’ complaints. A user commented that ‘Ads Notification is too bad’. Another user graded the app as ‘Ads in your notification bar... It is the most annoying thing ever!...’. Out of all UI related complaints, six ad reviews (2.3%) were about ad notifications.  

Intrusive: Another topic of ad UI complaints is related to whether ads interrupt the users’ interaction with an app. For example, if ads always popped up and needed a user’s confirmation, then the user could not play the app until confirming a yes or no dialog. Ads affecting the user experience of the app incurred negative reviews from users. A relatively large amount of ad UI reviews (13.4%: 35/262) complained about the intrusive ads. Following are two example complaints: ‘Ads are just too invasive. Uninstalled...’, ‘Ads interfere with use. The ads are intrusive and take over the app making it unusable. Its not possible to try it out to see if you would like to purchase it.’.  

Content: This topic deals with what is in the ads shown to users. Appealing ad content can help to catch users’ attention. However, we found evidence in the reviews to suggest a problematic aspect to this. Namely, users would complain when the content of an ad repeated or did not change. For example: ‘... I do however wish they weren’t the same ads every single time ...’, ‘Ad spam. The game is fine, but after every play i get spammed by the same video ad over and over. When i close one exactly the same one comes up after’. We found that 5.3% (14/262) of the UI related reviews that we examined were related to the content of ads.  

Timing: A sure-fire way to make a user see an ad is to place the ad on a landing page that is shown to the user when the app starts or before the next level in a game app. However, complaints from users indicate that this may affect users’ impressions of the app. For example: ‘Ad helish!! Just work to carry stupid ads after launching. And locks your screen without any interaction. Annoyance.’ and ‘Ads Ads Ads. As soon as I opened it, bang! Hit with an Amazon ad. That’s enough for me, uninstalling now!!’ were two of the reviews that we found regarding this practice. We found that 10.7% (28/262) of UI related complaints pertaining to having ads appear at an undesirable time.  

3) Non UI Related Ad Complaint Topics  

The distribution of non UI related ad complaint topics is shown in Figure 20. Overall, we found seven distinct non UI related complaint topics, each of which is shown in Figure 21 along with their frequency of occurrence in the reviews. Below, we describe the seven topics in more depth and give examples of users’ complaints about each topic.  

Blocking: This topic includes ads that disabled the normal functioning of an app. For example, when the ad is running, the execution of the host app is blocked and the end user cannot access the app’s primary functionality until the ad is interacted with by the user. These reviews were the most frequent in the non UI category and represented 30.2% (13/42) of non UI ad complaints. For example, one user stated that ‘Ads make it impossible to use. Ads refuse to play, so videos won’t load. Spent ten minutes switching between a few videos and couldn’t watch any.’.  

Paid: Besides publishing a ‘free but with-ads’ version of apps, developers usually provide paid apps that charge users for ad free functions. However, if these paid apps do not behave as expected and contain ads, this can cause user complaints. For example, a user complained that ‘Ads in paid version. Donated to remove ads, but they still show up. Emailed support, got no response...’. There were in total eight reviews (19%: 8/43) about this topic.  

Auto: For the purpose of executing some functions, in-app ads may automatically download files from remote servers or run in a special manner (e.g., turning on the audio and playing a downloaded audio file even though the device is in a muted state). Such behaviors can be considered malicious or extremely annoying. Once noticed, these ads incite complaints from users. Following is an instance, ‘Ads are truly annoying. I am really getting sick of the random auto launching of Playstore from within a game to suggest I download another game. Disappointing that a great game is being ruined by lousy marketing tactics’. In the review results, about (16.3%: 7/43) of non UI complaints were related to this topic.  

Crash: Sometimes ads are poorly implemented and are not
TABLE II: Large-scale analysis of ad reviews of apps in each category (total of 30) to identify ad complaint topics. We report the number of categories in which each ad complaint topic occurs among the top five.

| UI topics | # app categories | Non-UI topics | # app categories |
|-----------|------------------|--------------|------------------|
| frequency | 30               | paid         | 30               |
| timing    | 30               | auto         | 30               |
| location  | 28               | block        | 29               |
| intrusive | 24               | crash        | 29               |
| content   | 12               | slow         | 28               |
| popup     | 8                | battery      | 1                |
| blank     | 6                |              |                  |
| notification | 5          |              |                  |
| size      | 4                |              |                  |

compatible with app functionality. The end result is that the app keeps crashing. In this case, users cannot interact with any function of the app. There were several such complaints (16.3%: 7/43) in the result, such as ‘ad you put on crashes the game. Have to uninstall too many times. Fix the problem Or Stop using ad’.

Slow: The inclusion of mobile ads can slow the functionality of the app. The running of ads requires system resources, such as CPU and memory, which are limited on the mobile device. As a result, less resources can be allocated for the running of the host app, and this slows down the app’s execution. There were several reviews (9.3%: 4/43) complaining about this aspect. One example user complained that ‘Ads are irritating... Otherwise good app. Can anyone tell me how to block advertisements? It’s little bit slow too while operating.. Otherwise it would have been five stars’.

Privacy: In the mobile advertising ecosystem, ads inherit permissions from the host app. This allows ads to access sensitive information on the smartphone if the host app is granted the permission. However, users may be upset to learn that in-app ads obtain these permissions as well. Some examples include: ‘Ad supported apps suck. I absolutely refuse to install a free or ad supported app on my phone. The privacy intrusion and resource overload is unacceptable...’ and ‘Ads and permission. Ads and permissions granted are wrong’. There were several complaints (7%: 3/43) about this topic.

Battery: Mobile in-app ads consume extra resources on the system, such as energy. Components, such as display and network, are two of the most energy consuming components on a mobile device [17], [18], [19], [20]. These two components also serve an important role in the mobile ad ecosystem since they are used to retrieve and display ads. Even though energy consuming behavior is not directly linked to the app or the ads it contains, mobile ads routinely consume a significant amount of energy and extreme levels of resource consumption may trigger user complaints [6]. There was one such complaint on this topic (2.3%: 1/43): ‘Ads. Ads everywhere. Popups also. Expected battery drain’.

Additional Discussion: Our analysis of the 400 randomly selected reviews yielded sixteen distinct complaint topics. Despite being unable to similarly analyze the larger corpus of ad related complaints, we were interested in identifying if there were possibly additional topics that were undetected by our manual analysis. To investigate this, we used automated NLP based techniques to examine the larger corpus for clusters of ad complaint topics and compared this to our originally identified set.

To carry out this investigation, we applied the Word2Vec clustering technique to the textual contents of the ad complaint corpus. We used Word2Vec because in our comparison of NLP techniques, it performed most strongly at generating meaningful clusters (See Section V). Prior to running the clustering technique, we preprocessed the reviews through the following procedure: tokenizing words, removing useless symbols and stopwords (e.g., the, and, look), and stemming words. The output of running the NLP technique was a list of clusters, each of which contained a set of keywords that summarized the cluster. For each cluster, we calculated the relative word frequency and then used this to identify complaint topics associated with them and compared these topics to those identified by the manual categorization.

The clusters very closely matched the manual categorization with two exceptions. We found one cluster associated with complaints related to ads that appeared as blank space (blank) and another cluster related to ads whose display was tied to users’ participation in some sort of promotion activity (promotion). The first of these scenarios could occur when there is a change in the underlying ad unit ID (a unique ID generated by an ad network that identifies the app requesting ads to an ad network), the app’s included ad library has become obsolete, or there are connection problems between the app and MAN. The second scenario seems to occur when users participated in an activity with the purpose of obtaining an ad free experience, but the app still displayed ads in some capacity. Overall, the results of this larger scale indicate that the manually identified ad complaint topics are highly representative of the larger corpus of ad complaint reviews.

We would also like to confirm if the most popular ad complaint topics are consistent with their manual counterparts. Table II shows the top five ad complaint topics for each app category after the large-scale analysis. From the results, we can see that for UI related topics, frequency, timing, and location are the most common ad related complaint topics and are among the top three ad complaint topics for almost all of the 30 app categories. Meanwhile paid, auto, block, crash, and slow are the most common ad non-UI related complaint topics. This finding has the same trends as our manual categorization results.

V. THREATS TO VALIDITY

External Validity: The analysis in our study was based on reviews for only Android apps, so the results and conclusions may not generalize to other platform apps (e.g., iOS and Windows based), which also represent a significant portion of the app marketplace. However, we expect that since the underlying mechanisms of ad display are similar, we would see similar feedback from end users. In fact, developers implement several versions of an app that can be published on different platforms.
These versions share the same or similar functionality. In other words, the user experience of different versions of the app in most cases is comparable and the differences for end users are likely minor with respect to ads. Hence we argue that mobile in-app ads impact the user experience similarly across all platforms.

**Internal Validity:** We manually categorized ad reviews to obtain ad complaint topics. This process may be biased by human error or subjectivity and thus lead to incorrect tagging. To address this threat, we revisited each ad review several times after all reviews were initially categorized. In particular, each review was inspected at least three times. The other authors randomly inspected ad reviews to check the correctness of the categorization.

In addition, to confirm if the problems associated with ad complaints existed in their corresponding apps, we further conducted a qualitative study to validate these complaints. Such a study also enabled us to make an accurate categorization for reviews with vague or borderline descriptions. To do this, we installed and manually interacted with the apps corresponding to each of 400 ad related reviews. The apps that we interacted with were those for which we had access to the app’s primary functions as real users and could interact with long enough to ensure several ad reload cycles. We registered as a new user, if needed, before entering the main page. Once the ad aspects complained about by end users were confirmed in the app, we terminated the interaction. To ensure the ad functionality was fully loaded, each app was interacted with for at least 5 minutes unless the ad complaint was confirmed before that. The mobile device we used was a Samsung Galaxy SII smartphone with a rooted Android 4.3 operating system that is compatible with the original version of the APK file. We focused on the UI related features since they are more robust against the outside interference as compared to non-UI aspects. Our results showed that over 80% of ad complaints were confirmed for those apps that had ads displayed during the interaction. In other words, the problems associated with most ad complaints in the reviews exist in the corresponding apps. This further validates the conclusions of our analysis for each of the RQs.

**Construct Validity:** We applied Word2Vec to cluster ad complaint topics in each app category at a large scale. However, there may be other NLP techniques that are more suitable for such analysis. To mitigate the threat due to the choice of the NLP technique, we used the identified ad complaint topics in the manual analysis to evaluate the performance of three up-to-date NLP techniques. These were Word2Vec [21], K-means [22], and Latent Dirichlet Allocation (LDA) [23], all popular in the area of text understanding. Our results showed that Word2Vec identified the most complaint topics (15 out of the total 16), while K-means and LDA identified 9 and 12 complaint topics respectively. Although it is possible that other NLP techniques could identify even more, the goal of this study was not to identify the best possible NLP technique but to identify a reasonable one to use for the purposes of our RQs.

**VI. Directions for Future Work**

An important question to address in this paper is: what comes next? To answer this question we conducted an investigation to learn about how developers of the apps in our study have responded to their ad complaints over time. We began by downloading the latest versions of our subject apps (latest as of December 2016). In total, we were able to retrieve 322 of the 377 apps that corresponded to our reviews. For each of the apps for which we had been able to confirm the ad complaint, we installed the latest version of them on the same device we used to confirm the ad complaint and then interacted with it in the same way to attempt to reproduce the underlying ad problem. For each app, we recorded if the problem was reproducible in the latest version. We only focused on the apps that had confirmed UI related complaints since these could be easily confirmed by visual inspection.

We found that a significant majority of the apps still had the original ad related issue. More specifically, we found that 87% of the apps were unfixed, while for 13% of the apps we were unable to find the reported issue. Anecdotally, the fixed apps were typically highly popular apps (e.g., AngryBirds) with a large base of users, while the unfixed apps were typically much less popular.

These results raise interesting questions and motivate future work. In particular, we were struck by the fact that for so many apps, a significant and impactful topic of complaint had not been addressed. We hypothesize two possible explanations for this. First, developers may be unaware of the impact or the significance of ad related complaints. This hypothesis motivates further investigations into the impact of ad related complaints and the development and dissemination of guidelines that can be inferred from the complaints. Second, developers may be aware of the ad complaints, but believe they cannot change the app as that would lead to an unacceptable reduction in ad revenue. This hypothesis motivates further investigations into analyses that can help developers quantify the tradeoffs between maximizing mobile ad revenue and minimizing negative user experiences with ads.

**VII. Related Work**

In previous work [6], Gui and colleagues conducted an empirical evaluation on quantifying different costs of mobile ads. Among these costs, one was the impact of ads on app ratings. In that study, they observed that 4% of all complaints in app reviews were about ads. However, they did not categorize ad complaint topics or validate the ad related complaints in the corresponding apps. Ruiz and colleagues [24] examined the impact of ad libraries on ratings of Android mobile apps, and found that integrating certain ad libraries could negatively impact an app’s rating. While their work focuses on the ad library at the app level, ours is more fine grained and looks at the specific topics of complaints for ad related reviews.

A large amount of related studies have focused on user reviews and ratings at the app level. Palomba and colleagues [24] tracked how applications addressing user reviews increased their success in terms of rating. Specifically, they monitored
the extent to which developers accommodated crowd requests and follow-up user reactions as reflected in their ratings. Galvis Carreño and colleagues [26] relied on adapting information retrieval techniques to automatically extract topics from user comments. These topics were useful during the evolution of software requirements. AR-Miner [12] was proposed to analyze the content of user reviews. It was able to discern informative reviews, group and rank them in order of importance. Villarroel and colleagues [27] took a step further to design CLAP, an approach to automatically categorize user reviews into suggestions, cluster related reviews, and prioritize the clusters of reviews to be implemented in the next app release. Khalid and colleagues [5] studied user reviews from 20 iOS apps where they uncovered 12 types of user complaints. The most frequent complaints they found were functional errors, feature requests, and app crashes. ARdoc [28] and SURF [29] were proposed to summarize user reviews by classifying useful sentences. Iacob and colleagues designed [30] MARA, a prototype for automatic retrieval of mobile app feature requests from online reviews, and relied on LDA to identify common topics across feature requests. Guzman and colleagues [31] also used LDA to group fine-grained app features in the reviews. All of the above described work targets app level reviews, and does not directly categorize ad related reviews.

Another group of related work investigated ad fraud detection in mobile apps. PUMA [32] is a programmable framework that separates the logic for exploring app execution from the logic for analyzing app properties. One of its analyses was for ad fraud detection that identified small, intrusive, and too many ads per page. Similarly, DECAF [33] was designed and implemented to detect various ad layout frauds for Windows Store apps. Crussell and colleagues [34] developed an analysis tool, MAdFraud, which automatically ran many apps simultaneously in emulators to trigger and expose ad fraud by analyzing HTTP requests. In contrast to their work, we are not studying ad fraud or its impact, but rather examining ad related reviews and extracting ad complaint topics.

Previous studies of mobile ads have also been conducted from different perspectives. Gui and colleagues [35] proposed several lightweight statistical approaches to measure and estimate mobile ad energy consumption. Eprof [36] was presented as a fine-grained energy profiler for smartphone apps and was one of the first work to evaluate the energy consumption of third-party ad modules. Ruiz and colleagues [37] carried out a broad empirical study on ad library updates in Android apps. The results showed that ad library updates were frequent, and suggested substantial additional effort for developers to maintain ad libraries. Li and colleagues [38] investigated the use of common libraries in Android apps, and collected from these apps 240 libraries for advertisement. Liu and colleagues [39] explored efficient methods to de-escalate privileges for ad libraries in mobile apps. The system they developed contained a novel machine classifier for detecting ad libraries. Rasmussen and colleagues [40] analyzed the effects of advertisement blocking methods on energy consumption. None of these studies were concentrated on ad related reviews and ratings.

Another group of related work conducted surveys and proposed different methods or models to identify factors that influence consumers’ responses to mobile ads. Leppanen and colleagues [41] investigated factors, such as the marketing role of the mobile medium, development of technology, one-to-one marketing, and regulatory issues, which influence the acceptance of mobile advertising from both industrial and consumer points of view. With this information they built a conceptual model of consumers’ willingness to accept mobile advertising. Blanco and colleagues [42] suggested entertainment and informativeness as precursory factors of successful mobile advertising messages, after an empirical study using structural modeling techniques. Henley and colleagues [43] conducted a study to investigate college student exposure to and acceptance of mobile advertising in the context of an integrated marketing communication strategy, and found that incentives were a key motivating factor for advertising acceptance. In contrast to our study, these approaches are based on users’ response to mobile ads through surveys and focus on the psychology behind ad acceptance. We consider such studies to be complementary to our focus on identifying the top ad complaint topics.

VIII. CONCLUSIONS

Currently, millions of smartphone users download free apps from app stores and developers receive ad revenue by placing ads in these apps. In fact, ad revenue has become one of the most important sources for software developers to compensate for the cost of an app’s development. In this paper, we carry out experiments on a large scale dataset of mobile advertising to investigate what kind of ad aspects are complained about the most. We found that users complain about ad visual aspects more often than the non-visual aspects. We also found that in many app categories, the most common ad complaint topics are similar. Intuitively, more exposure of mobile ads to end users helps improve the chance of ad impressions/clicks that increase the ad revenue. But improper exposure is detrimental to the user experience of an app which in turn negatively impacts the ad revenue developers receive. App developers should carefully make a trade off to maximize their ad revenue.

Based on our study in this paper, we suggest that when developers design ad UI during the implementation, it will benefit them if they accommodate the following three criteria:

1) ad display timing: improper time or long duration (especially video ads) of ad display could cause a negative user experience;
2) ad display: some pages like the landing page may not be user friendly to display ads. The high frequency of ads among different pages is likely to distract the user’s attention, and thus result in end user complaints;
3) visual layout: displaying ads in visually obstructive locations (e.g., middle in the screen or close to clickable locations).
buttons) could interfere with the user’s interaction with the app.

When embedding ads into apps, developers should also pay attention to ad non-UI functions. In particular, it is not a good idea to display ads in the so-called paid version of an app, since this has a direct conflict with the expectations of users. Blocking app level functionality to focus attention on ads is another design decision that causes complaints by end users. Furthermore implementation decisions or lack of adequate testing that lead to the app crashing or slowing down the app’s running could also negatively impact the user experience with the app.

Our work suggests multiple areas for future work. In particular, we plan to correlate different ad aspects to app ratings so as to understand their relationship and identify more specific best practices with respect to mobile ads. We would also like to carry out controlled experiments and surveys that allow developers to determine the impact of their ad related choices on user ratings.

REFERENCES

[1] Number of Apps Available in Leading App Stores as of June 2016.
[2] O. Consulting. (2013, September) Marketer Perceptions of Mobile Advertising - 2013. Interactive Advertising Bureau.
[3] S. Vranica and C. S. Stewart. (2013, October) Mobile Advertising Begins to Take Off. Wall Street Journal.
[4] K. Saleh. (2015) Global Mobile Ad Spending - Statistics and Trends. Invesp.
[5] H. Khalid, E. Shihab, M. Nagappan, and A. E. Hassan, “What do mobile app users complain about?” IEEE Software, vol. 32, no. 3, pp. 70–77, 2015.
[6] J. Gui, S. McIlroy, M. Nagappan, and W. G. J. Halfond, “Truth in Advertising: The Hidden Cost of Mobile Ads for Software Developers,” in Proceedings of the 37th International Conference on Software Engineering (ICSE), May 2015.
[7] “https://admob.googleblog.com/2015/09/admob-banner-ad-implementation-guidance.html.”
[8] “http://www.mmaglobal.com/documents/best-practices.”
[9] “http://www.wordstream.com/adwords-mobile.”
[10] “https://support.google.com/admob/answer/2936217.”
[11] “https://support.mmediac.com/hc/en-us/articles/204610474-Best-Practices-for-Monetizing-Mobile-Applications.”
[12] N. Chen, J. Lin, S. C. Hoi, X. Xiao, and B. Zhang, “AR-miner: mining informative reviews for developers from mobile app marketplace;” in Proceedings of the 36th International Conference on Software Engineering (ICSE), 2014.
[13] S. McIlroy, N. Ali, H. Khalid, and A. E. Hassan, “Analyzing and automatically labelling the types of user issues that are raised in mobile app reviews,” Empirical Software Engineering, vol. 21, no. 3, pp. 1007–1106, 2016.
[14] “http://www.distimo.com/leaderboards/google-play-store/united-states/top-overall/free/month.”
[15] H. Khalid, M. Nagappan, E. Shihab, and A. E. Hassan, “Prioritizing the devices to test your app on: A case study of android game apps,” in Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering. ACM, 2014, pp. 610–620.
[16] F. Bea, “Why developers use interstitial ads to monetize iOS and Android apps,” appflood, September 2013.
[17] D. Li, S. Hao, J. Gui, and W. G. Halfond, “An Empirical Study of the Energy Consumption of Android Applications,” in Proceedings of the International Conference on Software Maintenance and Evolution (ICSME), September 2014.
[18] D. Li, A. H. Tran, and W. G. Halfond, “Making Web Applications More Energy Efficient for OLED Smartphones,” in Proceedings of the 36th International Conference on Software Engineering (ICSE). ACM, 2014, pp. 527–538.
[19] M. Wan, Y. Jin, D. Li, and W. G. J. Halfond, “Detecting Display Energy Hotspots in Android Apps,” in Proceedings of the 8th IEEE International Conference on Software Testing, Verification and Validation (ICST), April 2015.
[20] D. Li, Y. Lyu, J. Gui, and W. G. Halfond, “Automated Energy Optimization of HTTP Requests for Mobile Applications,” in Proceedings of the 38th International Conference on Software Engineering (ICSE), May 2016.
[21] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” arXiv preprint arXiv:1301.3781, 2013.
[22] J. A. Hartigan and M. A. Wong, “Algorithm AS 136: A k-means clustering algorithm,” Journal of the Royal Statistical Society. Series C (Applied Statistics), vol. 28, no. 1, pp. 100–108, 1979.
[23] D. M. Blei, A. Y. Ng, and M. I. Jordan, “Latent dirichlet allocation,” Journal of machine Learning research, vol. 3, no. Jan, pp. 993–1022, 2003.
[24] I. J. M. Ruiz, M. Nagappan, B. Adams, T. Berger, S. Dienst, and A. E. Hassan, “Impact of ad libraries on ratings of android mobile apps,” IEEE Software, vol. 31, no. 6, pp. 86–92, 2014.
[25] F. Palomba, M. Linares-Vásquez, G. Bavota, R. Oliveto, M. Di Penta, D. Poshyvanyk, and A. De Lucia, “User reviews matter! tracking crowdsourced reviews to support evolution of successful apps,” in Software Maintenance and Evolution (ICSME), 2015 IEEE International Conference on. IEEE, 2015, pp. 291–300.
[26] L. V. Galvis Carreño and K. Winbladh, “Analysis of user comments: an approach for software requirements evolution,” in Proceedings of the 2013 International Conference on Software Engineering. IEEE Press, 2013, pp. 582–591.
[27] L. Villarroel, G. Bavota, B. Russo, R. Oliveto, and M. Di Penta, “Release planning of mobile apps based on user reviews,” in Proceedings of the 38th International Conference on Software Engineering. ACM, 2016, pp. 14–24.
[28] S. Panichella, A. Di Sorbo, E. Guzman, C. A. Visaggio, G. Canfora, and H. C. Gall, “ARdoc: app reviews development oriented classifier,” in Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering. ACM, 2016, pp. 1023–1027.
[29] A. Di Sorbo, S. Panichella, C. V. Alexandru, J. Shimagaki, C. A. Visaggio, G. Canfora, and H. C. Gall, “What would users change in my app? summarizing app reviews for recommending software changes,” in Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering. ACM, 2016, pp. 499–510.
[30] C. Iacob and R. Harrison, “Retrieving and analyzing mobile apps feature requests from online reviews,” in Mining Software Repositories (MSR), 2013 10th IEEE Working Conference on. IEEE, 2013, pp. 41–44.
[31] E. Guzman and W. Maalej, “How do users like this feature? a fine grained sentiment analysis of app reviews,” in Requirements Engineering Conference (RE), 2014 IEEE 22nd International. IEEE, 2014, pp. 153–162.
[32] H. Hao, B. Liu, S. Nath, W. G. Halfond, and R. Govindan, “PUMA: Programmable UI-Automation for Large Scale Dynamic Analysis of Mobile Apps,” in Proceedings of the 12th annual international conference on Mobile systems, applications, and services (MobiSys). ACM, 2014, pp. 204–217.
[33] B. Liu, S. Nath, R. Govindan, and J. Liu, “DECAF: Detecting and Characterizing Ad Fraud in Mobile Apps,” in Proceedings of the 11th USENIX Symposium on Networked Systems Design and Implementation (NSDI), 2014.
[34] J. Crussell, R. Stevens, and H. Chen, “MadFraud: Investigating ad fraud in android applications,” in Proceedings of the 12th annual international conference on Mobile systems, applications, and services. ACM, 2014, pp. 123–134.
[35] J. Gui, D. Li, M. Wan, and W. G. Halfond, “Lightweight measurement and estimation of mobile ad energy consumption,” in Proceedings of the 5th International Workshop on Green and Sustainable Software. ACM, 2016, pp. 1–7.
[36] A. Pathak, Y. C. Hu, and M. Zhang, “Where is the energy spent inside my app? Fine Grained Energy Accounting on Smartphones with Eprof,” in Proceedings of the 7th ACM european conference on Computer Systems, 2012.
[37] I. J. M. Ruiz, M. Nagappan, B. Adams, T. Berger, S. Dienst, and A. E. Hassan, “On ad library updates in Android apps,” IEEE Software, 2014.
[38] L. Li, J. Klein, Y. Le Traon et al., “An investigation into the use of common libraries in android apps,” in 2016 IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER), vol. 1. IEEE, 2016, pp. 403–414.
[39] B. Liu, B. Liu, H. Jin, and R. Govindan, “Efficient Privilege De-escalation for Ad Libraries in Mobile Apps,” in Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys). ACM, 2015, pp. 89–103.

[40] K. Rasmussen, A. Wilson, and A. Hindle, “Green Mining: Energy Consumption of Advertisement Blocking Methods,” in Proceedings of the 3rd International Workshop on Green and Sustainable Software, 2014.

[41] M. Leppaniemi and H. Karjaluoto, “Factors influencing consumers’ willingness to accept mobile advertising: a conceptual model,” International Journal of Mobile Communications, 2005.

[42] C. F. Blanco, M. G. Blasco, and I. I. Azorín, “Entertainment and informativeness as precursory factors of successful mobile advertising messages,” Communications of the IBIMA, pp. 1–11, 2010.

[43] M. Hanley and R. E. Boostrom Jr, “How the Smartphone is Changing College Student Mobile Content Usage and Advertising Acceptance: An IMC Perspective,” International Journal of Integrated Marketing Communications, vol. 3, no. 2, 2011.