Erasing Labor with Labor: Dark Patterns and Lockstep Behaviors on the Google Play Store

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ABSTRACT

Google Play Store’s policy forbids the use of incentivized installs, ratings, and reviews to manipulate the placement of apps. However, there still exist apps that incentivize installs for other apps on the platform. To understand how install-incentivizing apps affect their users, we examine their ecosystem through a socio-technical lens and perform a longitudinal mixed-methods analysis of their reviews. We shortlist 60 install-incentivizing apps which collectively account for over 160.5M installs on the Google Play Store. We collect 1,000 most relevant reviews on these apps every day for a period of 52 days. First, our qualitative analysis reveals various types of dark patterns that developers incorporate in install-incentivizing apps to extort services and build market at the expense of their users. Second, we highlight the normative concerns of these dark patterns at both the individual and collective levels, elaborating on their detrimental effects on the price transparency and trust in the market of Google Play Store. Third, we uncover evidence of install-incentivizing apps indulging in review and rating fraud. Building upon our findings, we model apps and reviewers as networks and discover lockstep behaviors in the reviewing patterns that are strong indicators of review fraud. Fourth, we leverage the content information of reviews to find that reviewers who co-review more apps also show greater similarity in the content of their reviews, making them more suspicious. Finally, we conclude with a discussion on how our future work will generate implications for Google Play Store to prevent the exploitation of users while preserving transparency and trust in its market.

KEYWORDS

Google Play Store, Dark Patterns, Fraud

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1 https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/
2 https://www.statista.com/statistics/734332/google-play-app-installs-per-year/
3 https://www.statista.com/statistics/986536/mobile-app-install-advertising-spending-global/
4 https://support.google.com/googleplay/android-developer/answer/989864
in the top charts and at least six times more likely to witness an increase in their install counts. While their work focuses on measuring the impact of incentivized installs on the Google Play Store, our work aims to develop an understanding of how it affects the users of install-incentivizing apps. To this end, we perform a longitudinal mixed-methods analysis of the most relevant reviews of 60 install-incentivizing apps collected daily over a period of 52 days. Our ongoing work makes the following contributions:

1. Our qualitative analysis provides a detailed overview of the various dark patterns used by install-incentivizing apps to deceive users. We situate them in past literature to highlight various normative concerns that disrupt the individual and collective welfare of users on Google Play Store.

2. We uncover evidence of install-incentivizing apps indulging in review and rating fraud, following which we discover three types of lockstep behaviors that are strong indicators of fraud – (i) groups of apps sharing common reviewers, (ii) groups of reviewers reviewing common apps, and (iii) writing similar reviews across common apps.

2 DATASET

We created queries by prefixing “install apps” to phrases like “earn 150,086 unique reviewers. Each review was then stored in a local MongoDB instance along with four attributes:

- apps
- rating
- timestamp
- thumbsUpCount

We adopted an inductive open coding approach to thematically code these reviews [6]. In the first iteration, the first and second authors independently worked on identifying high-level codes for these reviews which were then compared and discussed among all researchers. During this process, we defined the ‘completion of offers on install-incentivizing apps’ as an act of labor by users and the ‘incentive promised for their labor’ as value. Then, we reached a consensus on four high-level themes: exploitation, UI challenges, satisfaction, and promotion, which we define below:

1. **Exploitation**: User invests labor but is unable to gain value.
2. **UI Challenges**: User invests labor but the app’s UI makes it challenging for them to gain value.
3. **Satisfaction**: User invests labor and is able to gain value.
4. **Promotion**: Review contains promotional information about the user and/or the app.

The first three themes were far more prevalent in our data and particularly useful for capturing the inter-relationship between a user’s labor and its value. Next, we performed two iterations of line-by-line coding of reviews within the high-level themes where the researchers identified emerging patterns under each theme until the principle of saturation was established.

3 QUALITATIVE ANALYSIS

To understand the various ways in which install-incentivizing apps affect their users, we performed qualitative analysis of their reviews. First, we sampled only the top four most relevant reviews for all 60 apps from December 10, 2021, to January 10, 2022, owing to their default visibility, obtaining 1,825 unique reviews. Then, we adopted an inductive open coding approach to thematically code these reviews [6]. In the first iteration, the first and second authors independently worked on identifying high-level codes for these reviews which were then compared and discussed among all researchers. During this process, we defined the ‘completion of offers on install-incentivizing apps’ as an act of labor by users and the ‘incentive promised for their labor’ as value. Then, we reached a consensus on four high-level themes: exploitation, UI challenges, satisfaction, and promotion, which we define below:

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3.1 Findings

In this section, we describe our findings from the qualitative analysis, elaborating on the commonalities and differences of patterns within high-level codes that we discovered using line-by-line coding.

3.1.1 Exploitation and UI Challenges.

Reviews under high-level codes ‘exploitation’ and ‘UI challenges’ explicitly describe the dark patterns present in install-incentivizing apps that make it impossible/difficult for users to redeem value for their labor; dark patterns are tricks embedded in apps that make users perform unintended actions [1]. First, our low-level codes uncover the different types of dark patterns present in reviews of install-incentivizing apps. Then, we ground these types in prior literature [5] by utilizing lenses of both individual and collective welfare to highlight their normative concerns. The individual lens
focuses on dark patterns that allow developers to benefit at the expense of users whereas the collective lens looks at users as a collective entity while examining expenses. In our case, the former comprises three normative concerns. First, patterns that enable developers to extract labor from users without compensating cause financial loss (I1) to users. Second, cases where the data of users is shared with third parties without prior consent, leading to invasion of privacy (I2). Third, when the information architecture of apps manipulates users into making certain choices due to the induced cognitive burden (I3). The lens of collective welfare facilitates understanding of the bigger picture of install-incentivizing apps on Google Play Store by listing three additional concerns. Due to high competition (C1), some developers incorporate dark patterns in apps that empower them to ‘extract wealth and build market power at the expense of users’ [2] on the platform. In conjunction with their concerns at the individual level, they also pose a serious threat to the price transparency (C2) and trust in the market (C3) of Google Play Store. In Table 1, we show these different types of dark patterns mapped to their individual and collective normative concerns using sample reviews from our data.

3.1.2 Satisfaction and Promotion.
Most reviews coded as ‘satisfaction’ were relatively shorter and lacked sufficient context to explain how the app benefitted the user, for e.g. “Good app”, “Nice App”, “Very easy to buy money”, “Nice app for earning voucher”. We performed Welch’s t-test to validate that the number of words in reviews coded as satisfaction were very highly significantly lower than reviews coded as exploitation or UI challenges ($p < 0.001, t = –11.41$). The shorter length of reviews, along with the excessive use of adjectives and unrelatedness to the apps represented key spam-detection signals [10], raising suspicions about their fraudulence. We discovered evidence of the same in some reviews coded as ‘promotion’ – “Gets high rating because it rewards people to rate it so”, “I rated it 5 stars to get credits.” Other reviews coded as ‘promotion’ involved users promoting other competitor apps (“No earning I task complete not give my wallet not good! CHASADA App is good fast earning is good go install now thanks”) or posting their referral codes to get more credits within the install-incentivizing app (“The app is Awesome. Use My Referral Code am****02 to get extra coin”).

### Table 1: Different types of dark patterns mapped to their individual [Financial Loss (I1), Invasion of Privacy (I2), Cognitive Burden (I3)] and collective [Competition (C1), Price Transparency (C2), Trust in the Market (C3)] normative concerns.

| High-Level Code | Low-Level Code | Review | Normative Concerns |
|-----------------|----------------|--------|--------------------|
| Exploitation    | Withdraw Limit | 100000 is equal to 10 dollars. just a big waste of time. You can not reach the minimum cashout limit. | ✓ |
|                 | Cannot Redeem  | Absolute scam. Commit time and even made in app purchases to complete tasks ... I have over 89k points that it refuses to cash out! RIP OFF MERCHANTS! They ignore all communication too! | ✓ |
|                 | Only Initial Payouts | Good for the first one week then it will take forever to earn just a dollar. So now I quit this app to save my precious time. | ✓ |
|                 | Paid Offers     | I was given a task in which I had to deposit 30 INR in an app and I would receive 150 INR as a reward. I was told to wait for 24 hrs. 5 days have passed and every time I mail I am just told to be patient. | ✓ |
|                 | Hidden Costs    | Most surveys say that the user isn’t eligible for them, after you complete them! Keep in mind you may not be eligible for 90% of the surveys. | ✓ |
|                 | Privacy Violations | If you enter your phone number into this app then you’ll be FLOODED with spam texts and scams. I woke up this morning to a whopping 17 spam texts!!! I might have to change my phone number because I unwittingly trusted this pathetic scam app. | ✓ |
| UI Challenges   | Too Many Ads    | Pathetic with the dam ads! Nothing but ads!!! Money is coming but only pocket change. If’ll be 2022 before I reach $50 to cashout, if then. You pay the players pennies on the dollar when the ad revenue is probably thousands of dollars per day in your pockets. | ✓ |
|                 | Progress Manipulation | I redownload the app since the app would crash all the time ... I logged in and guess what?? ALL MY POINTS ARE GONE... 2 days grinding and getting 12K points all gone... are you kidding me? | ✓ |
|                 | Permission Override | When you give it permission to go over other apps it actually blocks everything else on your phone from working correctly including Google to leave this review. | ✓ |
from users in the form of offers. We highlight how these patterns disrupt the welfare of users, depleting the trust and transparency of Google Play Store. We discover three different types of lockstep behaviors exhibited by apps and reviewers that strongly indicate fraud. Both types of frauds (incentivized installs and reviews) are only made possible by the labor of vulnerable users who are exploited or crowd-workers who are underpaid [7]. This enables the developers to extract profits as they get away with violating Google’s policies without any consequences or accountability. Thus, we aspire to identify what facilitates the continued exploitation of users despite their reviews, and characterize how these two types of frauds co-construct each other on the platform. To this end, we conjecture that fraudulent positive reviews by crowd-workers under install-incentivizing apps suppress the ranks of reviews containing exploitative experiences of users and plan to explore the same in our future work.

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5 CONCLUSION AND FUTURE WORK

Our current work sheds light on various types of dark patterns that developers incorporate in install-incentivizing apps to extort labor

Figure 4: (a) Network of apps showing labels of the top five apps with the most common reviewers; (b) co-clustered matrix for apps and (c) co-clustered matrix for reviewers exhibiting lockstep behaviors; (d) pairwise cosine similarity matrix of reviewers arranged in the same order as (c), showing how clusters of reviewers write similar reviews.