Does Variety Drive Engagement in Short-Form Digital Content? Insights from Glance

Marketing Dynamics Conference Submission

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Motivation and Research Questions

- Short-form content on digital platforms is extremely popular (e.g., TikTok, YouTube Shorts, Instagram Reels) and generates billions in yearly ad revenue
- Firms invest significant resources in the design of algorithm-based recommender systems, need to balance learning consumer preferences and diversification
- Predictions from theory and recent evidence are mixed:
  - Literature on satiation and variety-seeking suggests consumers prefer diverse content (Nelson et al. 2009), variety can improve content recommendations (Song et al. 2018) and mobile ad response (Rafieian et al. 2020)
  - Consumers also enjoy similar content in succession, i.e., binge-watching (Lu et al. 2024), rabbit hole effect (Woolley et al. 2022)
  - Consumer preferences change, state-dependent preferences for diversity/assimilation (Shi et al. 2025)

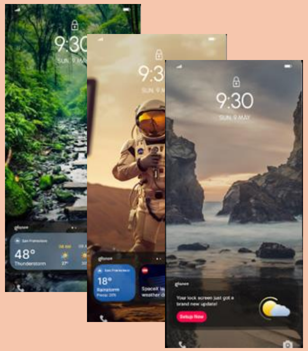
Research Questions:

- What is the effect of increasing variety on the consumption of short-form media content?
- What are the underlying mechanisms driving consumer response to content diversification?

Empirical Setting: glance

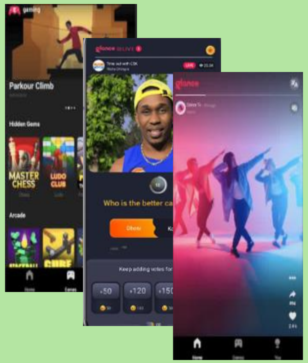
- Glance: Online app pre-installed on over 250 million Android smartphones in India
- Provides users with dynamically updated content **cards** in the user's lockscreen when whenever they "glance" at their phone
- Cards contain an attractive image with small amounts of text, based on current events (news, sports), trending topics (pop culture), and more timeless content (travel, food)
- Can view cards in Lockscreen or Binge Mode (requires swiping into app)
- Main source of revenue: Selling display ad spots on news articles, video content, games (requires users to click/tap on a card)

Lockscreen Mode:
Wallpaper cards on phone lockscreen, refreshes by locking/unlocking phone



Users can switch between modes

Binge Mode:
Similar card content within the app, view new cards by swiping left/right



Users can click/tap on any card to engage further (e.g., news article). **Firm earns revenue from display ads.**

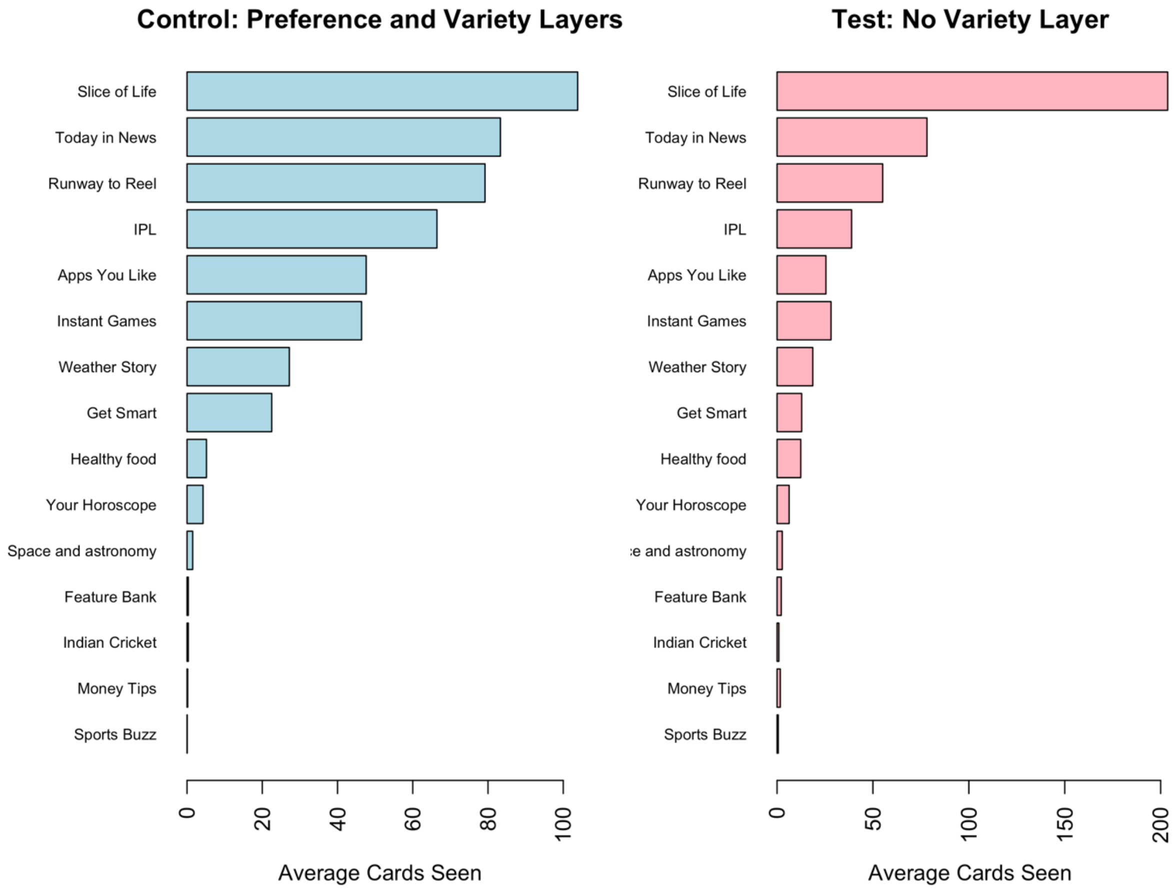
Card Serving Algorithm

- 15 main categories of cards
- Two layers of card serving algorithm:

(1) Preference layer: Glance learns user preferences for card categories based on past clicking behavior, recommends similar content to previously clicked content based on card image embeddings (i.e., each card is assigned a rank based on “relevance” to user)

(2) Variety layer: To broaden user interests and prevent user over-exposure to the same category, a set proportion of cards are shown from each category (i.e., cards “re-ranked” to inject variety);

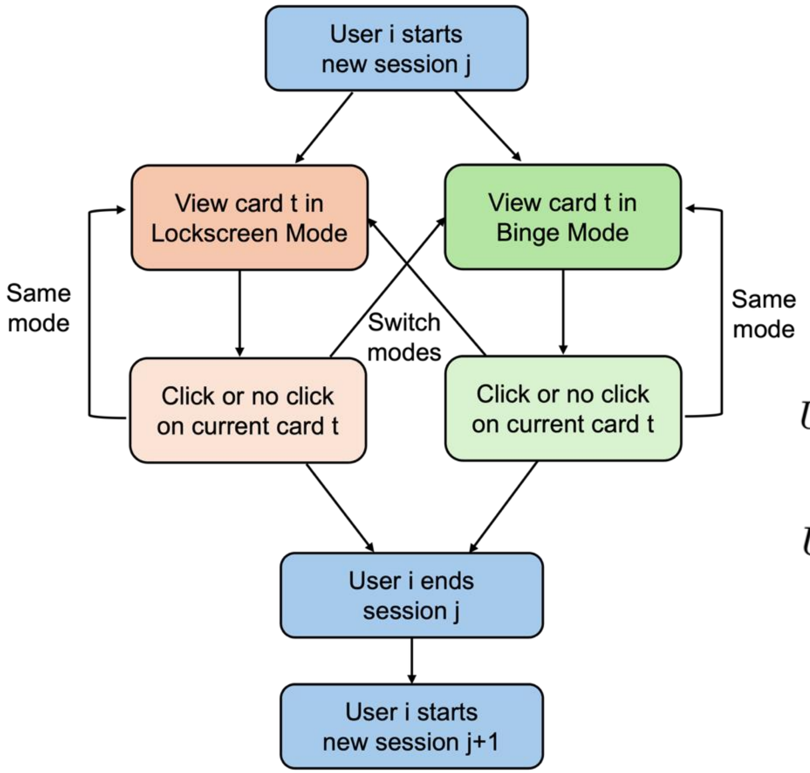
Removing variety layer results in concentration of most popular category (Slice of Life)



Overview of Empirical Approach and Results

- Analyze Glance browsing behavior of 149,268 unique users for one week
- Estimate a statistical model that captures card browsing and click decisions, satiation/variety-seeking preferences for different card categories; model exploits natural variation in distribution of categories across sequences of cards shown to users within sessions
  - **Main finding: Users have a strong preference for repeated similar content**
  - **Counterfactual simulations suggest that reducing category variety would increase overall content consumption and clicks**
- Large-scale field experiment where half of users were randomly assigned to a test condition where the variety layer of card serving algorithm was turned off (i.e., reducing category variety) for three weeks
  - **Main finding: Consistent with counterfactual simulations, reducing category variety increased the number of cards viewed and clicked**
  - **However, greater engagement came at the expense of variety in engagement: users tended to click on a much less diverse set of content categories**
  - **Further analysis suggests that category preferences are malleable: for a subset of users with strong preferences for “game” cards, tended to substitute game cards with other categories that became more prominent when variety layer removed**

Data and Model



$$\mathcal{L}(\theta_i) = \prod_{j=1}^{J_i} \underbrace{P(\text{InterSessionTime}_{ij})}_{\text{Proportional hazard model}} \prod_{t=1}^{T_{ij}} \underbrace{P(\text{Mode}_{ijt}) \times P(\text{Click}_{ijt}) \times P(\text{Continue}_{ijt})}_{\text{Binary logits}}$$

Conditional on Browsing Mode:

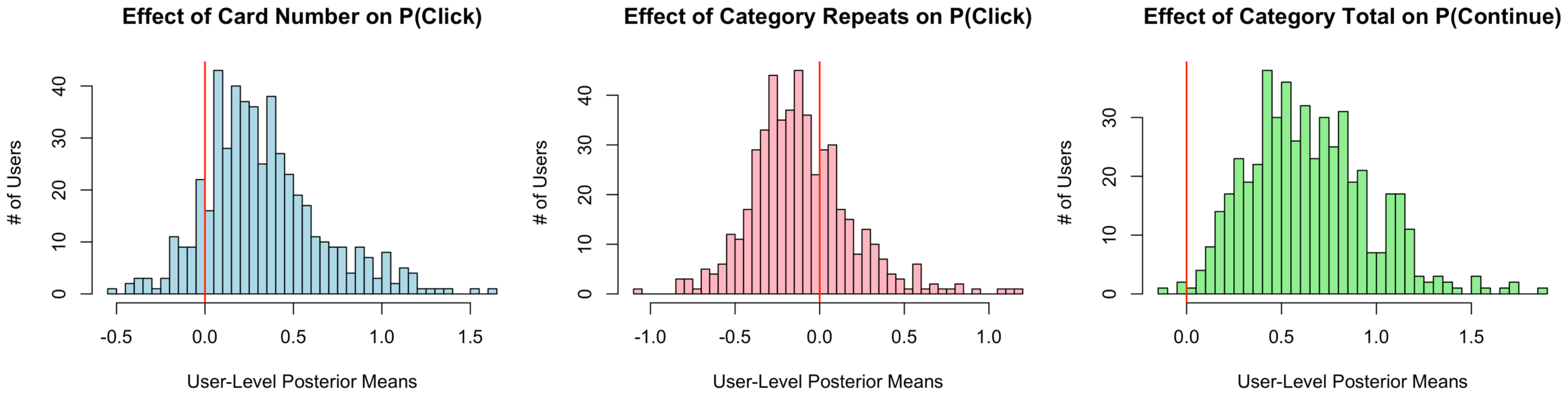
$$U_{\text{Click},ijt} = \alpha_{i0} + \alpha_{i1}\text{NumCards}_{ijt} + \alpha_{i2}\text{CategoryRepeat}_{ijt} + \sum_k \gamma_{ik}\mathbb{1}(\text{Category}_{ijt} = k) + \epsilon_{Click,ijt}$$

$$U_{\text{Continue},ijt} = \beta_{i0} + \beta_{i1}\mathbb{1}(\text{Click}_{ijt} = 1) + \underbrace{\beta_{i2}\text{CategoryTotal}_{ijt}}_{\text{Number of cards from the current card's category so far in session}} + \sum_k \delta_{ik}\mathbb{1}(\text{Category}_{ijt} = k) + \epsilon_{Continue,ijt}$$

*Note: Following results presented for **Lockscreen Mode**, similar results for Binge Mode*

Model Estimation Results

- Hierarchical Bayes (MCMC) estimation on subsample of 10,000 users, uninformative priors, assume parameters come from MVN
- **Lockscreen mode:** seeing more cards from the same category increases likelihood of continuing the session, resulting in more cards seen and more clicks



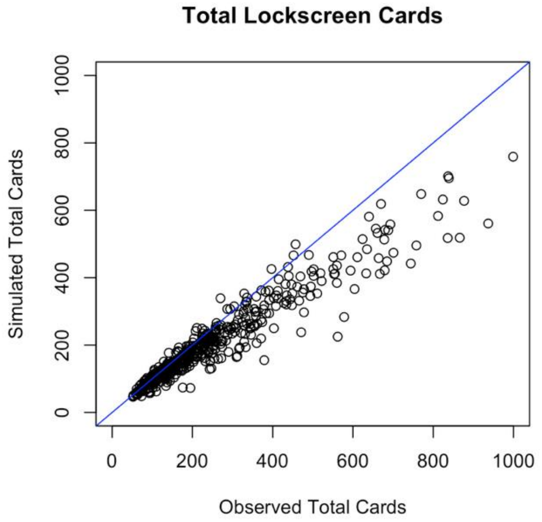
PPCs and Counterfactual Simulations

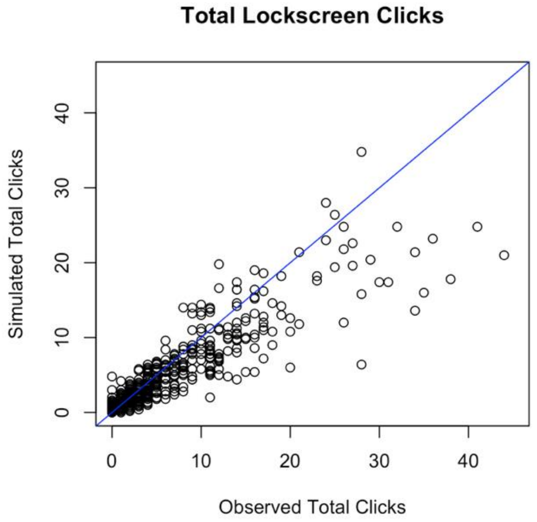
Posterior Predictive Checks (PPCs):

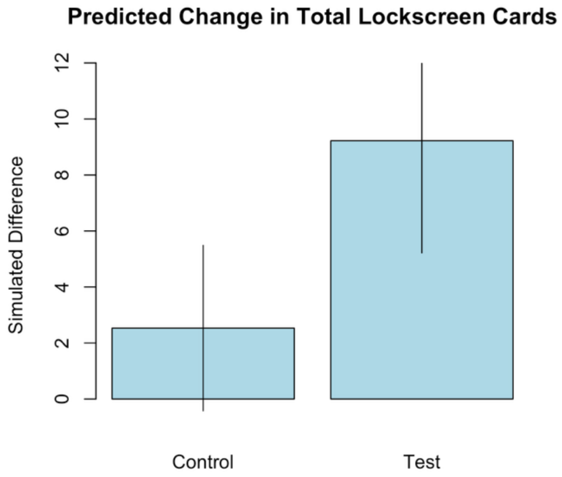
- Model captures full data generating process, can use model parameters to simulate sessions, total cards viewed, and total clicks
- Simulated vs. observed metrics show that model is able to capture heterogeneity across users.

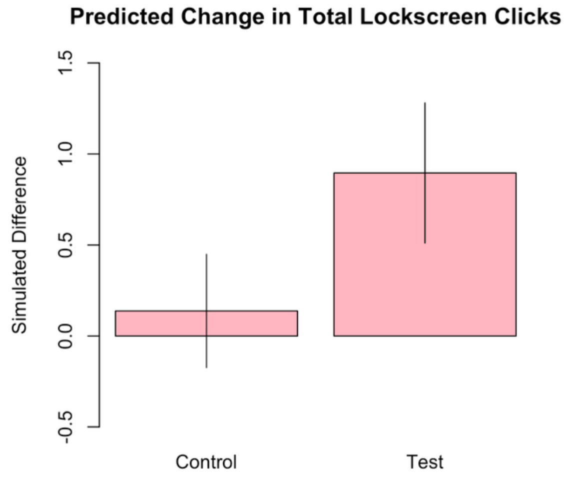
Counterfactual Simulations:

- Simulate total cards viewed and clicks when users are presented the next set of cards during Week 2
- **Control condition**: Same serving algorithm, includes preference and variety layers
- **Test condition:** Variety layer removed
- Predict more cards viewed and clicked in test condition (due to preference for more cards from same category)

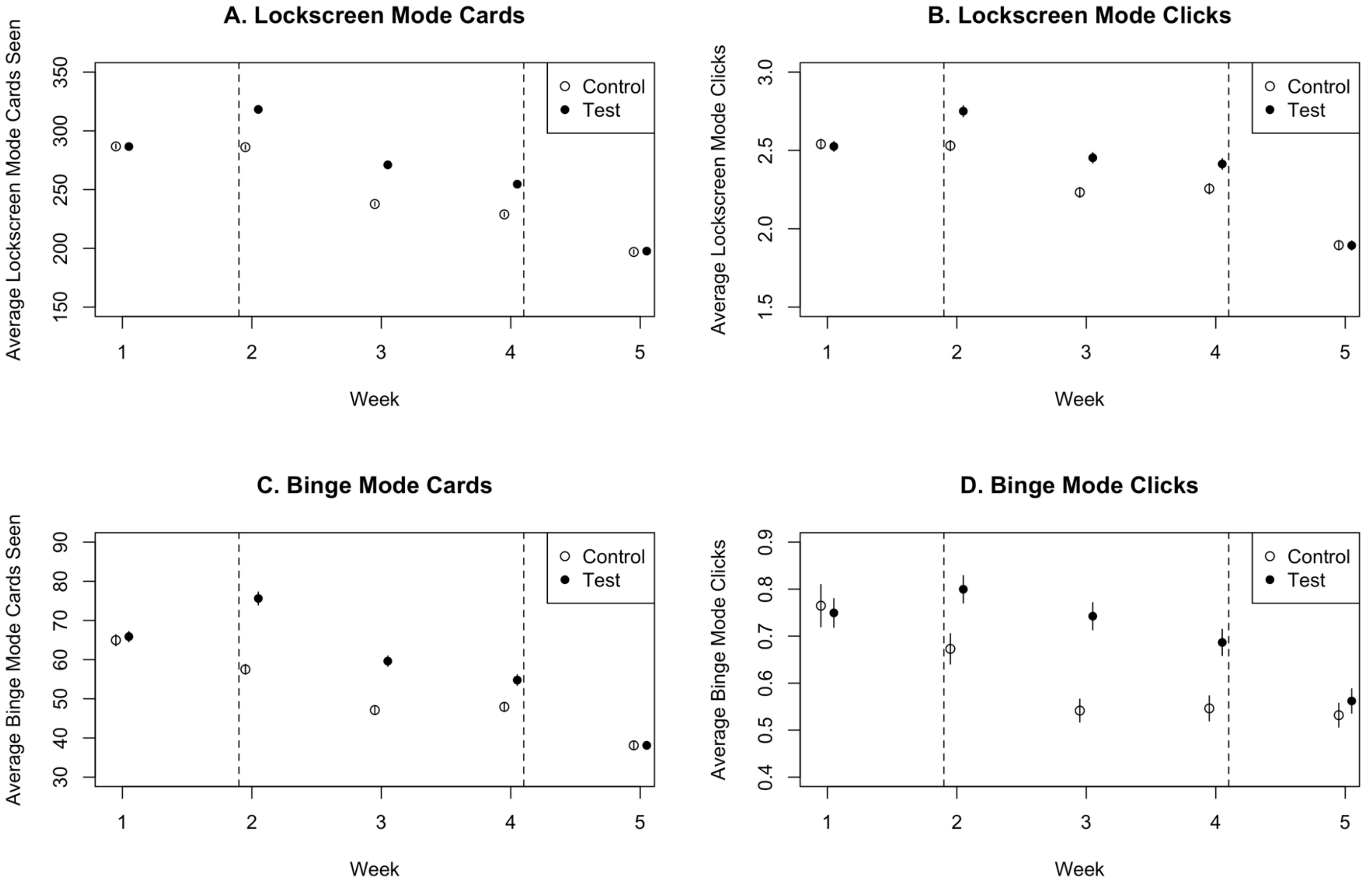








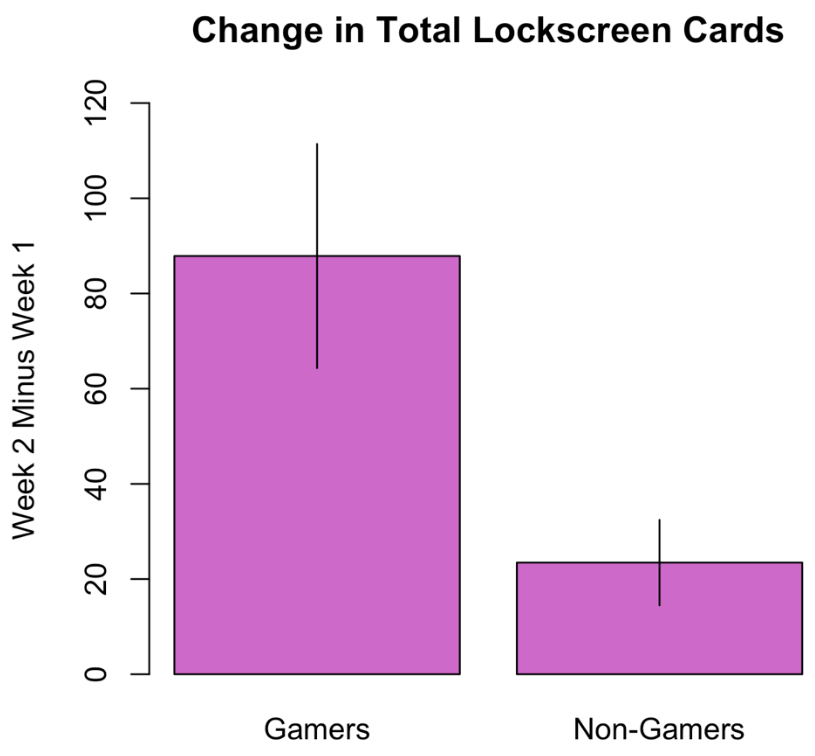
Field Experiment Results



- Tracked 149,268 for 5-week period, field experiment ran during weeks 2-4
- Test condition turned off variety layer
- Turning off variety layer resulted in greater engagement in terms of total cards viewed and clicks (as predicted in counterfactual simulations)
- However, users clicked on a much less diverse set of card categories, clicks were more concentrated on the most popular categories.
- Changes in category click distribution suggest that preferences in short-form content settings are highly malleable

Malleable Preferences and Future Directions

- Subset of users with high engagement in instant game cards ("gamers") exhibit the highest increase in cards seen when variety layer is removed (i.e., see fewer game cards, more Slice of Life cards)
- This suggests that category preferences are malleable, with users quickly finding content category substitutes to consume
- Future directions:
  - Investigate differences between lockscreen mode (more cards viewed, lower click rate) vs. binge mode (fewer cards viewed, higher click rate)
  - Use card image embeddings as additional measure of variety, more granular than card categories
  - Follow-up field experiment where variety in the sequence of cards is increased (i.e., maximized by effectively "scrambling" a given sequence)



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