

## Supplementary Material

### Nonparametric Tests

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### Nonparametric Tests

#### *Differences in Coded Tweets After the Approval of Descovy*

Among coded tweets (N = 1008), Mann-Whitney U tests were conducted to compare differences in the Theory of Planned Behavior (TPB) constructs (Fishbein & Ajzen, 2011) and source before and after the approval of Descovy. These nonparametric tests were conducted to further ensure the robustness of these results.

**TPB Constructs.** There were significantly more information tweets about PrEP after the approval of Descovy than before,  $U = 116193.5$ ,  $p = .003$ . Further, there were significantly less tweets discussing barriers to PrEP after the approval of Descovy,  $U = 106727$ ,  $p < .001$ . There were no significant differences in

attitudes ( $p = .247$ ), norms ( $p = .113$ ), perceived behavioral control ( $p = .157$ ), and intentions/behavior ( $p = .111$ ) after the approval of Descovy.

**Specific Barriers.** Among tweets discussing barriers to PrEP, there were significantly less tweets discussing costs after the approval of Descovy than before,  $U = 121057$ ,  $p = .040$ . Further, there were significantly less tweets discussing access after the approval of Descovy than before,  $U = 114241$ ,  $p < .001$ . There were no differences in issues with pharmaceutical company ( $p = .237$ ) and stigma ( $p = .393$ ).

**Source Type.** There were no differences in source type (individual versus organization) before and after the approval of Descovy ( $p = .692$ ).

### *Differences in Coded Tweets between Source Type*

Among coded tweets ( $N = 1008$ ), Mann-Whitney U tests were conducted to compare differences in TPB constructs by source type (individual versus organization). These nonparametric tests further ensure the robustness of these results.

**TPB Constructs.** There were significantly more informational tweets posted by organizations than individuals,  $U = 71445.5$ ,  $p < .001$ . In addition, there were significantly more tweets expressing attitudes posted by individuals than organizations,  $U = 88168.5$ ,  $p < .001$ . Further, there were significantly more tweets expressing intentions/behavior posted by individuals than organizations,  $U = 87403.5$ ,  $p < .001$ . There were no differences between source type for norms ( $p = .994$ ), perceived behavioral control ( $p = .065$ ), and overall barriers ( $p = .422$ ).

**Specific Barriers.** Among barrier tweets, there were significantly more individual tweets about costs ( $U = 12439.5$ ,  $p = .013$ ) and stigma ( $U = 13503.5$ ,  $p = .016$ ) compared to organizational tweets. However, there were significantly more organizational tweets that discuss access compared to individual tweets,  $U$

= 11563,  $p < .001$ . There were no differences regarding issues with pharmaceutical company by source type ( $p = .938$ ).

### *Differences in Emotions and Sentiments after the Approval of Descovy*

For the full dataset ( $N = 16139$ ), Mann-Whitney U tests were conducted to compare differences in positive emotion, negative emotion, anxiety, anger, and sadness before and after the approval of Descovy. These nonparametric tests further ensure the robustness of these results.

***Positive and Negative Emotion.*** There were significantly more tweets that expressed positive emotion after the approval of Descovy than before,  $U = 30240973$ ,  $p < .001$ . However, there were no significant differences in negative emotion ( $p = .576$ ).

***Discrete Emotion.*** There were significantly less tweets that expressed anger after the approval of Descovy than before,  $U = 31923004.5$ ,  $p < .001$ . However, there were significantly more tweets that expressed sadness after the approval of Descovy than before,  $U = 32293740$ ,  $p = .041$ . There were no significant differences in anxiety ( $p = .543$ ).

### *Differences in Emotions and Sentiments by Source Type*

Mann-Whitney U tests were conducted to compare differences in positive emotion, negative emotion, anxiety, anger, and sadness by source type (individual vs. organization). These nonparametric tests further ensure the robustness of these results.

***Positive and Negative Emotion.*** Tweets posted by individuals expressed significantly more positive emotion than organizational tweets,  $U = 86531$ ,  $p = .014$ . However, there were no significant differences in negative emotion ( $p = .638$ ).

***Discrete Emotion.*** Organizational tweets expressed significantly more anxiety compared to individual tweets,  $U = 90177$ ,  $p = .018$ . However, there were no significant differences in anger ( $p = .159$ ) or sadness ( $p = .832$ ).

### Removing “Bots”

In the following analyses, we ran Botometer (Sayyadiharikandeh et al., 2020), a bot classification tool based on a machine learning algorithm that outputs a score indicating whether a tweet was made from a human or a bot. Complete Automation Probability (CAP) scores provide the probability (from 0 to 1) that an account with a X% score or greater is likely a bot. Scores closer to 0 indicate that the tweet was likely from a human, and scores closer to 1 indicate that the tweet is likely from a bot account. We utilized a cutoff CAP score of 80% and re-ran analysis to examine any discrepancies between the “no bot” sample and the full coded sample. It is important to note that though this machine learning tool has been trained and extracts over 1000 different features to determine bot score (Botometer, 2021), these tools are not perfect and may incorrectly classify some tweets. For example, organizations that post content systematically may be identified as a bot by the classifier.

Tables S1-4 display the re-run analyses with only the “no bot” sample. Results remain consistent among all but one finding. In the “no bot” sample, there was not a significant difference in access tweets before and after the FDA approval; however, these findings should be taken with caution. This may be likely due the smaller sample size of barrier tweets or potentially by an error in the bot classification of the tweets.