



# ONWARD

## Findings, Metrics, and Methodology: Porn Overuse Study

Copyright, Onward Method Inc, 2017

# Summary

- Onward enrolled **1366** self-identified porn overusers in a 4 month trial.
- **89% of Pro Users (with Smart Filter) reduced or arrested their trackable usage.**
- **62% of Pro users reduced the frequency of attempted use.**
- **60% of Pro users have continued activity after 30 days.**
- **We predicted acting out better than chance for 79% of users.**
- 81% of all users accepted our tracking technology.
- Users form an Onward habit by their 10th daily check-in that is sticky.
- Specific, strong emotional states predict incidents of acting out.
- Dating/Porn comorbidity is low, duration & frequency are uncorrelated, and self-reports are inaccurate. These reinforce our more measurement-driven, algorithmic approach and focus on overuse instead of addiction.



# Findings and Analysis

Clinical and Data Science at Onward

The Onward App: Usage and Engagement

Users' Habits, Trends, and Findings

Program Efficacy and Changes Over Time

# Clinical Advisory Board

## Timothy Fong, M.D.

Director, UCLA Addiction Medicine Clinic and Director, Addiction Psychiatry Fellowship

Co-Director, UCLA Gambling Studies Program

Associate Clinical Professor, Psychiatry and Biobehavioral Sciences

Neuropsychiatric Institute and Hospital, UCLA

## Richard J Rosenthal, M.D.

Co-Director, UCLA Gambling Studies Program

Clinical Professor, Psychiatry and Biobehavioral Sciences

David Geffen School of Medicine, UCLA

## Christina Brezing, M.D.

Substance Abuse Fellow, Columbia University Medical Center



COLUMBIA UNIVERSITY  
MEDICAL CENTER



# Findings and Analysis

Clinical and Data Science at Onward

The Onward App: Usage and Engagement

Users' Habits, Trends, and Findings

Program Efficacy and Changes Over Time

# Onward: Acquisition, Feature Set, and Timeline

Using Google and Reddit ads, we recruited 1366 self-identified porn overusers on iOS and Mac to a free trial of Onward.

## Date and First Feature Release

**Sep:** Daily Check-ins, Reporting, and Chat

**Nov:** Blocking and Skills

**Dec:** Educational Content

**Jan:** Accountability, MI, Friend Connect

We measure usage directly from users' internet traffic; they do not self-report. Users self-report affect information as a part of their chat conversation.



# Feature Usage Breakdown

The following represents major feature usage in Onward

## Tracking:

**80.9 ± 2.1%** of app users enabled the VPN

## Blocking:

**88.8 ± 3.0%** of users who encountered the option to block enabled the blocker.

## Snoozing:

**31.3 ± 4.6%** of users who have enabled blocking have also snoozed the blocker.

## Accountability Sharing:

**25.3 ± 9.7%** of users have added an accountability partner after starting the AS script.



# Note: Demographic Information

For [privacy reasons](#), we have made a conscious decision not to collect demographic information from participants. We believe this approach enhances willingness to share honestly, though we may begin asking for more information in the future.

This includes:

- Potential information available via the acquisition funnels (Google AdWords; Reddit Advertising)
- In-app questions or questionnaires

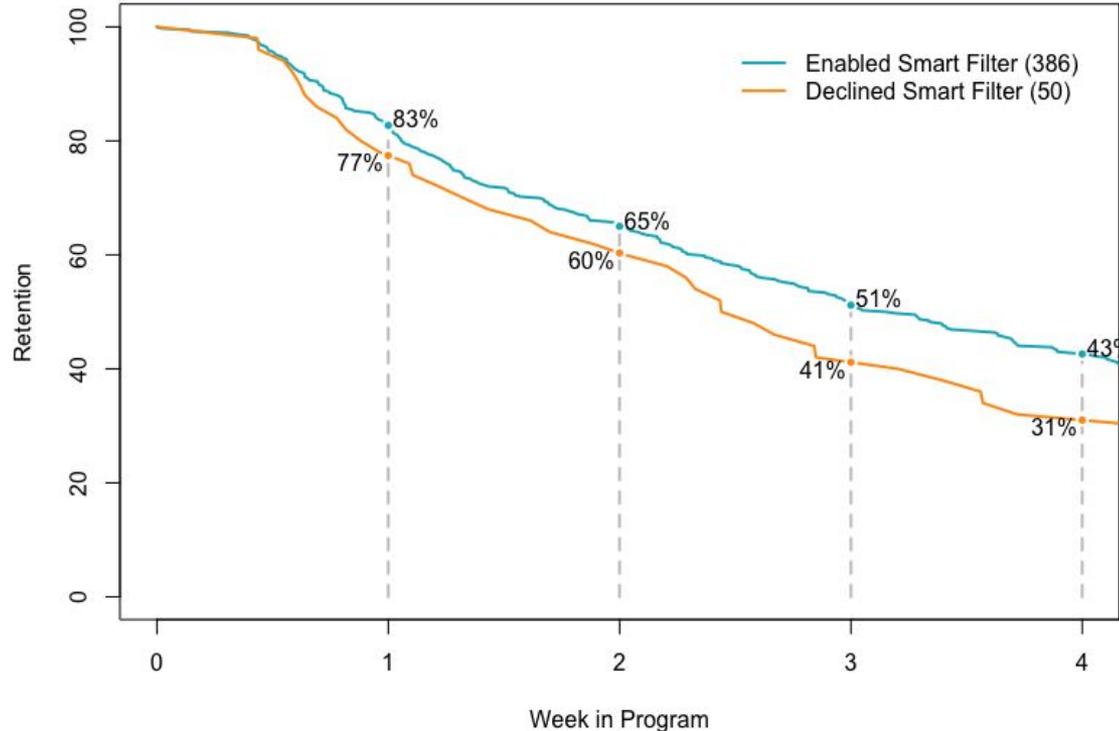
# Users who Block are More Motivated to Remain

Smart Filter blocks unwanted content and apps and is offered on Day 3 of the program. Users who enable it have a higher, long-term retention rate:

- **434** of our 1366 users completed their introduction to the Smart Filter. This **32%** is a lower limit on the number of users who progress sufficiently into the program to receive the 3rd daily check-in.
- **386** of these 434 users choose to engage the filter, that is, **89%** acceptance.

Roughly **42%** of the individuals who enable blocking seem committed to the program in the long term as compared to **31%** of those who opt out.

## User Retention by Smart Filter Choice





# Findings and Analysis

Clinical and Data Science at Onward

The Onward App: Usage and Engagement

**Users' Habits, Trends, and Findings**

Program Efficacy and Changes Over Time

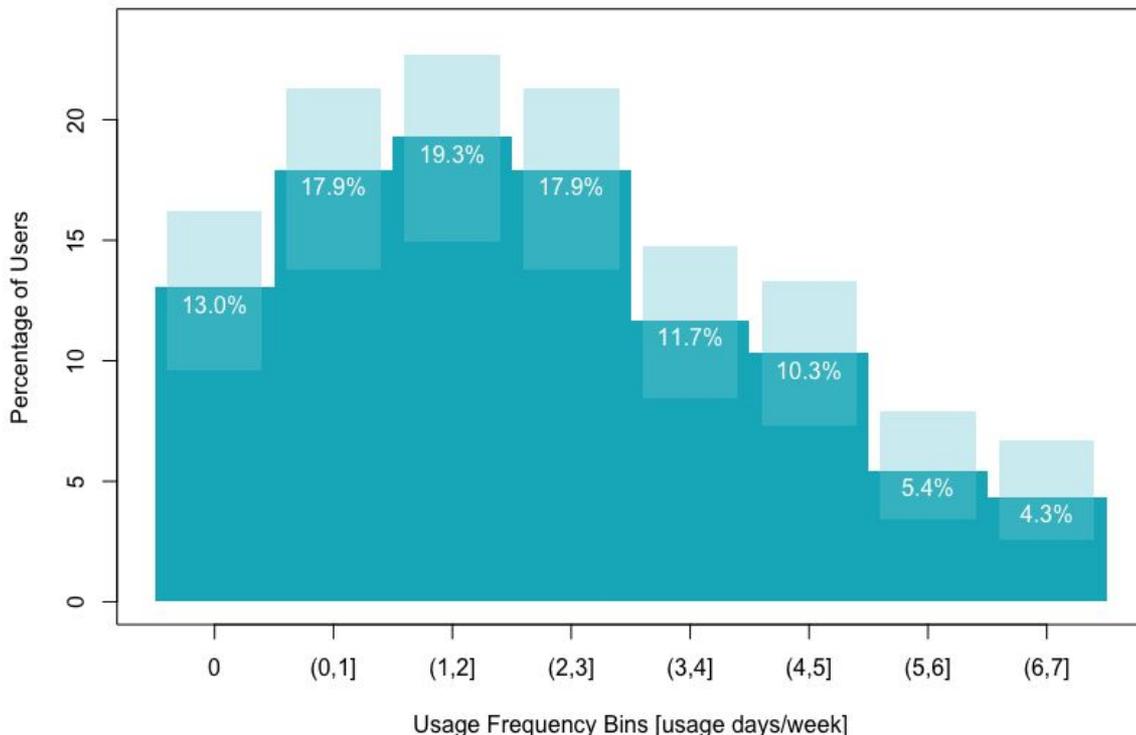
# Overuse Terminology Matters Due to Frequency

Of 1366 users, **368** logged more than a week's worth of usage without the Smart Filter. Their "natural" usage frequency is lower than might have been expected:

- A user's "usage frequency" is the average number of days per week they access porn on an iOS device.
- The median usage frequency is **2.0 days/week** and two-thirds of users fall in the range between 0.4 to 4.4 days per week.
- Light teal bars indicate 95% CI in light teal (we neglect uncertainty in individuals' usage frequencies; bin uncertainties are correlated)

Overuse may be a better term than addiction because many users act out infrequently while still believing they want to change.

## Weekly Porn Usage Frequency



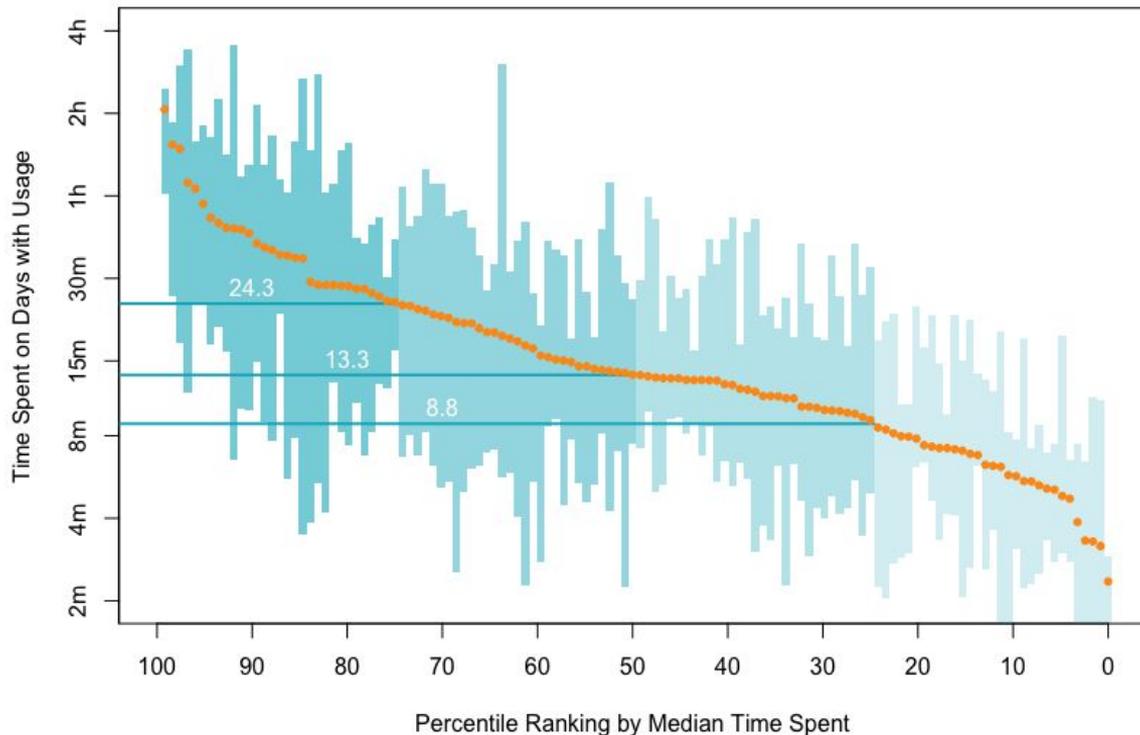
# Time Spent Consuming Is Lower Than Expected

We additionally study time users spend consuming on their usage days:

- We plot the spread in the time users spend per usage day for those 124 users who accumulated seven or more usage days without the Smart Filter.
- Orange points mark each user's median daily usage; teal bars show the range of times within which falls two-thirds of each user's time spent.
- Users in the highest quartile of median daily usages are greater than 24.3 min. The next quartile lies above 13.3 min and the third above 8.8 min.

For clarity, we have not included users with fewer usage days, though we observe comparable figures for larger sets.

## Consumption Time on Usage Days



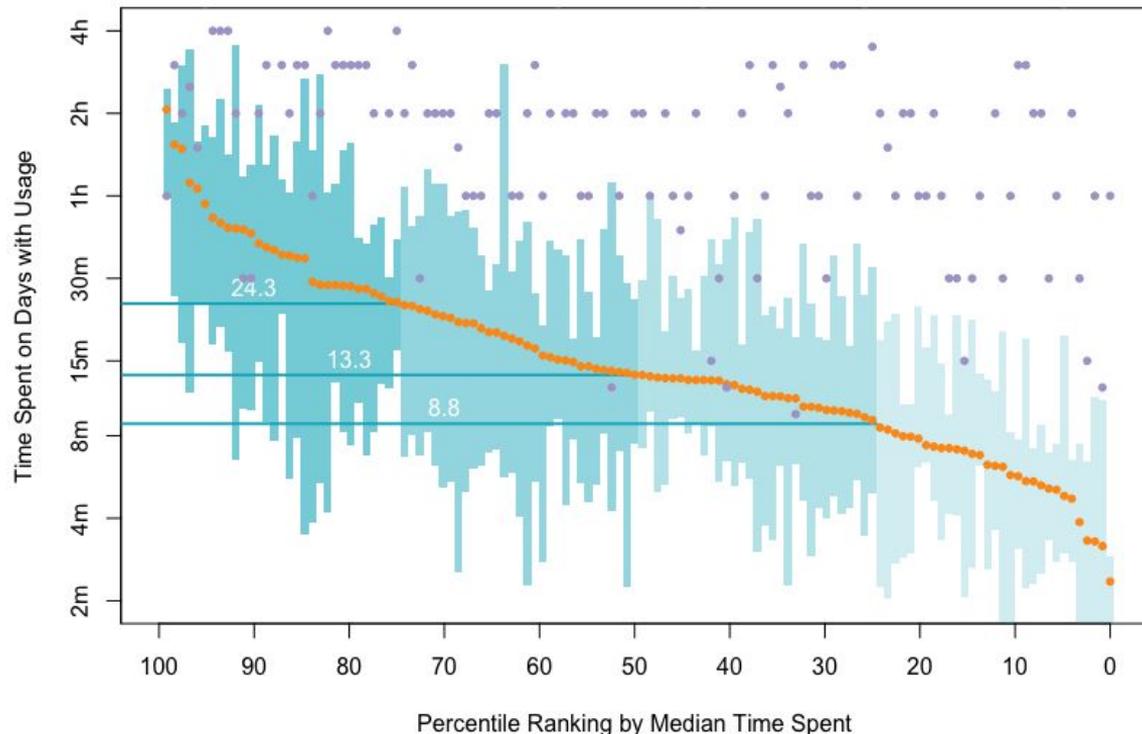
# The Importance of Measured vs. Self-Report Data

The gold standard of clinical research in addiction has been self-reported data. Onward is in the unique position to compare users' directly measured usage and their self-reported estimate.

Purple points overlaid on the time-spent plot show that **87%** of users wildly exceed our tracking measurements.

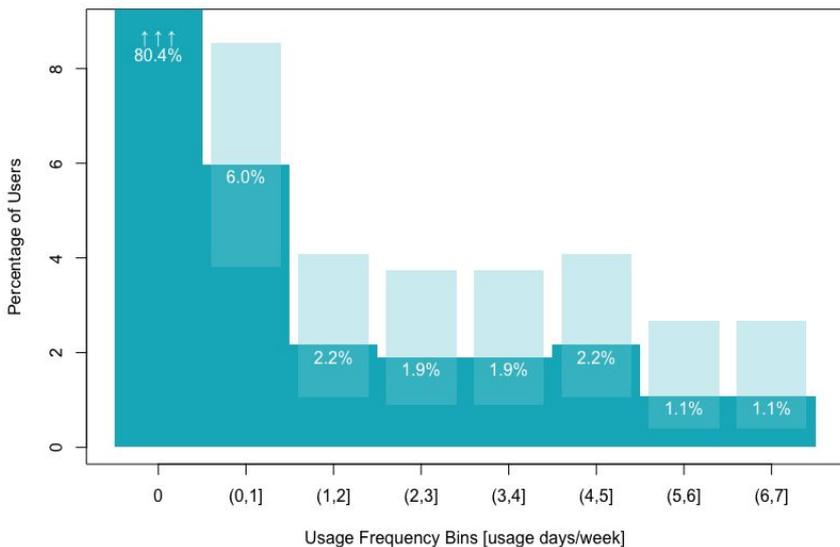
This reinforces the importance of direct measurement vs self-reporting and respect for users' self-definition of problem thresholds.

Only **13%** of these users estimated a usage time that fell between the 17th and 83rd percentile of their actual usage (that is, have their purple point within their teal bar).

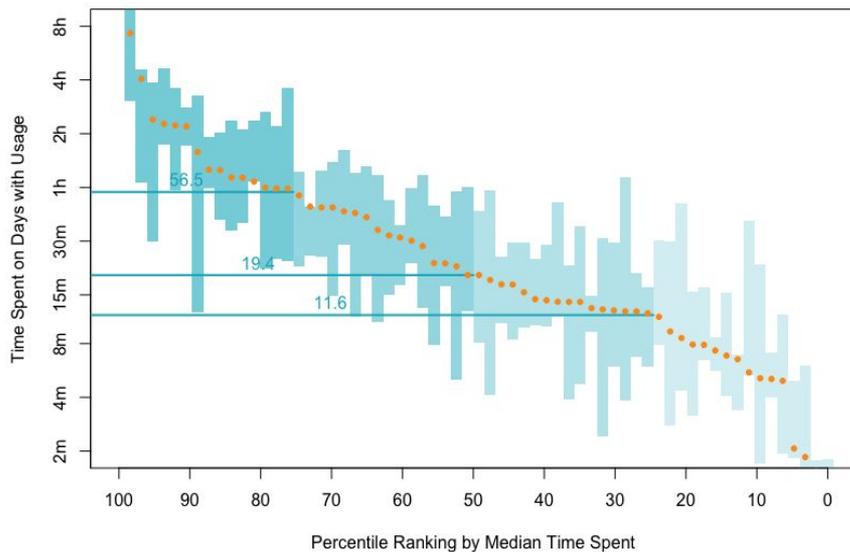


# The Few Who Use Dating Apps Spend More Time

## Weekly Dating Usage Frequency



## Dating Median Usage



Over **80%** of our users (who self-identified with **porn** overuse) did not engage dating sites or apps.

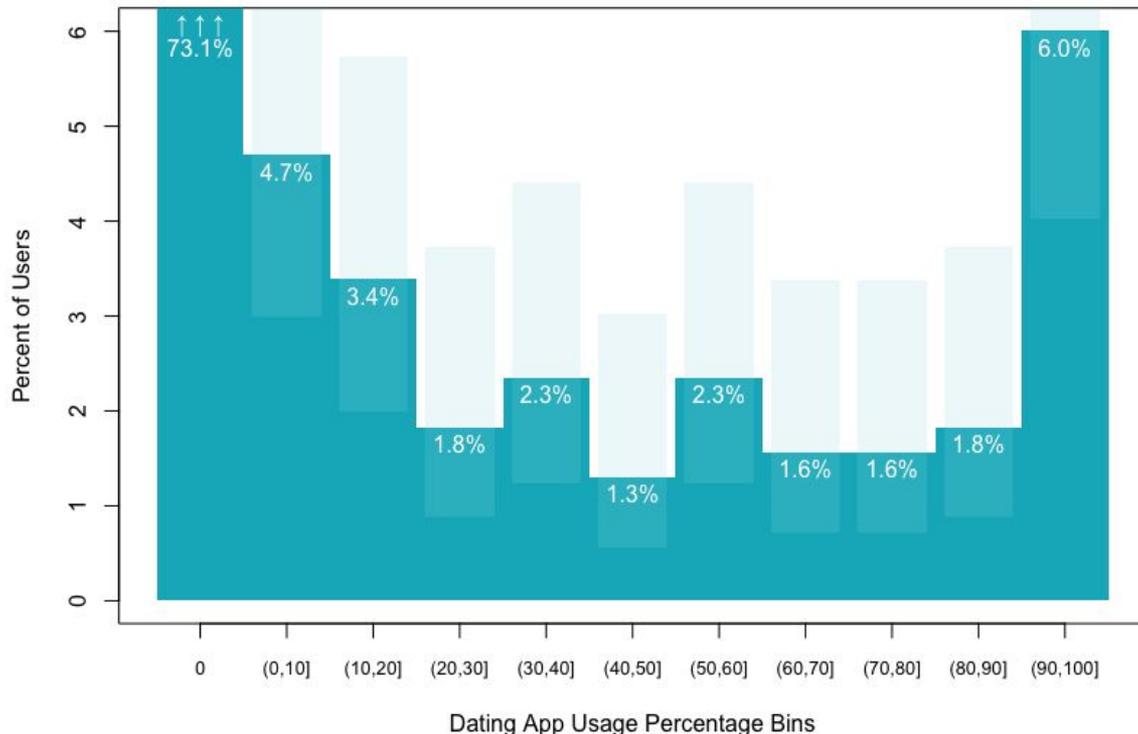
However, those that do **spend roughly twice as much time** as porn users of comparable percentile.

# Porn and Dating Overuse Comorbidity is Low

## Dating Factor Fraction

Our opening gambit tracked [porn](#) and [dating/hookup site](#) traffic under the assumption that overuse of one might occur alongside overuse of the other. It seems this is infrequent in our population.

Here, we give users a “[porn factor](#)” (their average daily porn consumption over the median of all porn users’ average daily porn consumption) and a similarly defined “[dating factor](#)” and bin based on the fraction of their total usage factor that is their dating factor. Calculations include only users with 7 or more days of any activity.



# Time Spent, Weekly Frequency are Uncorrelated

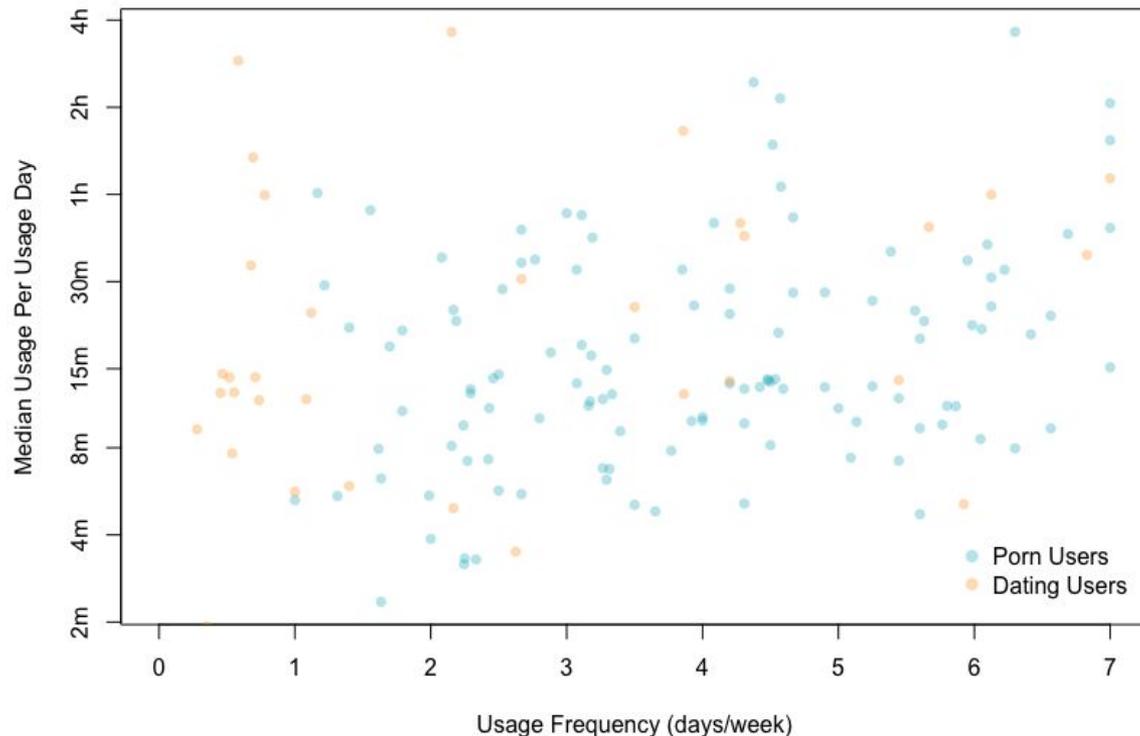
The frequency of days on which a user acts out and their median time spent on usage days are not well-correlated.

Each teal or orange point represents a single user's porn or dating site usage data, respectively, as calculated in the previous slides. Independent of the choice of a linear, log-linear, or log-log model, the Pearson correlation coefficients for porn and dating site usage indicate no notable correlations:

	Porn	Dating
Linear	0.26	0.28
Log-Linear	0.31	0.36
Log-Log	0.28	0.36

Data includes all users with 4 or more distinct days of internet traffic data.

## Users' Median Usage v. Frequency



# Note: Historical Stereotypes

Onward initially offered porn and dating as a single solution vertical. Based on the lack of correlation between these categories, we no longer offer the two as a coupled solution.

While we treat these historically defined overuse categories as logical starting points, this revelation suggests that emerging data will fundamentally redefine the overuse categories and subgroups.

Our data-driven approach at Onward maximizes our flexibility in addressing overuse as we move past historical stereotypes.



# Findings and Analysis

Clinical and Data Science at Onward

The Onward App: Usage and Engagement

Users' Habits, Trends, and Findings

Program Efficacy and Changes Over Time

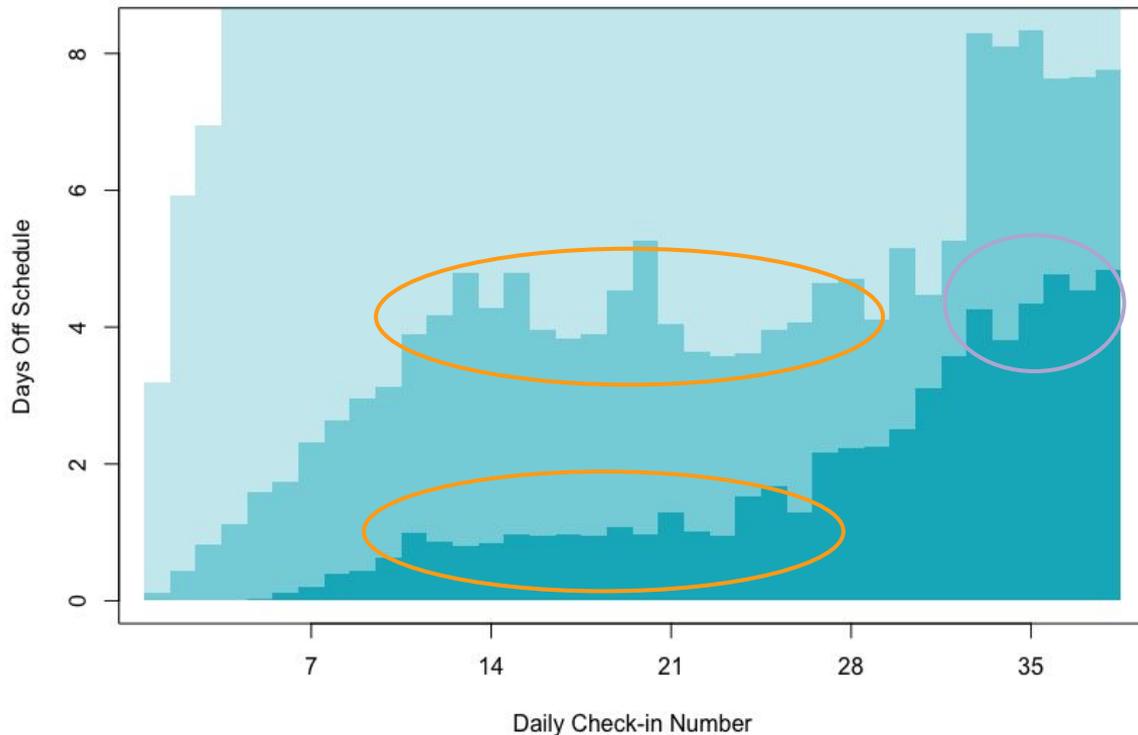
# Onward Builds Habits & Adherence in Two Weeks

At the center of the Onward Method is a user's commitment to checking in daily. We visualize on the right the degree to which users stick with this commitment, counting the number of days missed at each daily check-in.

- The height of the lower, dark teal bars shows the commitment of the 17% most adherent users. For example, This top sixth is less than 5 days off schedule by their 35th check-in (purple ellipse).
- 50% of users are off track by no more than the height of the middle bars at each check-in; 87% fall below the top bars (which exceed the plot's range).

Users who continue past roughly their 10th check-in **tend to stay on schedule** for another two weeks (orange ellipses), showing a greater commitment to daily adherence.

## Days Off Schedule v. Check-in



# Prediction of User Behavior is Improving

Onward pushes a daily notifications to users' devices to encourage daily adherence. Using a predictive algorithm, we individually schedule each user's daily notifications to maximize our chances at catching them "just in time" and thereby reduce porn usage.

Each user's habits are different: while some users regularly use at the same time each day, others act out at more or less random times. In these situations, one can assess prediction efficacy by estimating the number of users for whom our method will "correctly" predict a session more frequently than another model. We consider three alternative models:

- A randomly chosen notification time.
- A quasi-random time that attempts to account for users' waking hours.
- A 9pm local-time notification (the even hour that precedes the greatest number of our users' sessions).

Our schema predicts **better than a random time** for **79% of our users**, **better than a quasi-random time** for **70% of users**. I estimate that we also predict **better than the static 9pm time** for roughly **43% of users**.

The efficacy of the Smart Filter (as described later) complicates the predictive power of this schema; the method requires additional development to address the interplay between these features.

# Affect May Predict Behavior and Vice Versa

During each daily check-in, we ask users to describe their current mood using an emoji<sup>†</sup>.

Correlating these affect reports with the incident of porn usage in the preceding or following **4 hours**, we find that:

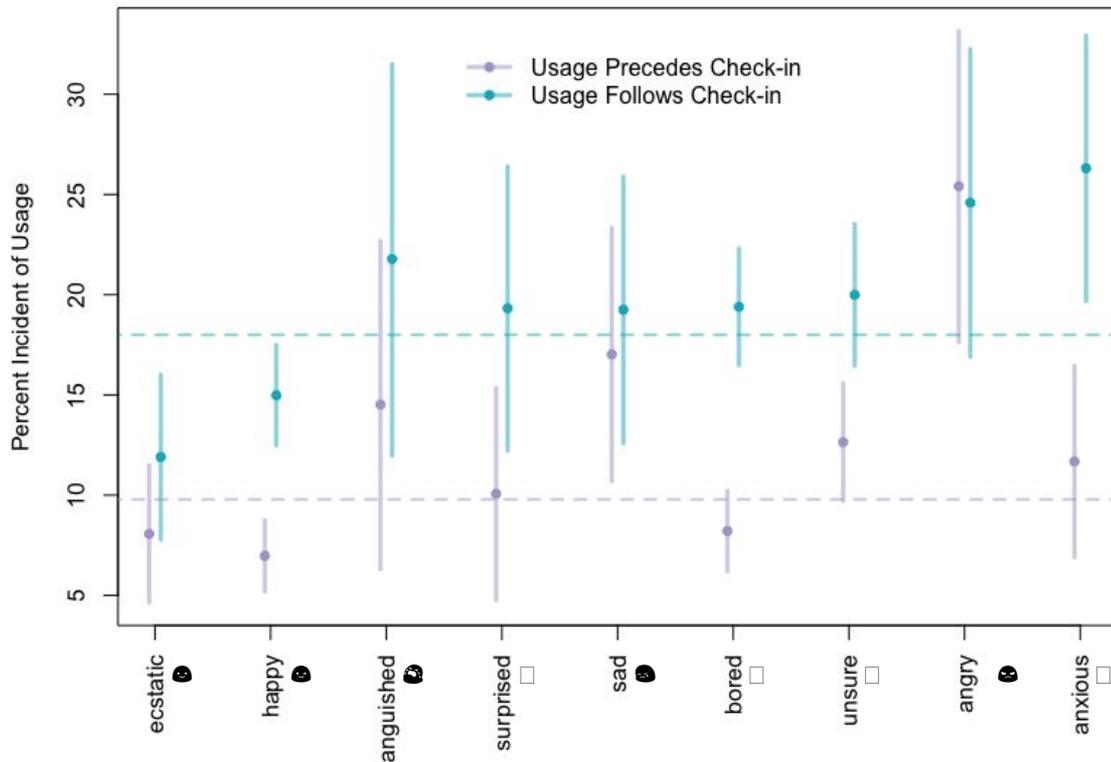
- When usage **precedes check-in**, users are **more likely**<sup>‡</sup> to feel 😬 or 😞.
- When users feel 😬 or 😞, they are **less likely**<sup>‡</sup> to use in the **immediate future**;
- After ☐ reports, users are **more likely**<sup>‡</sup> to use in the **immediate future**.

Note that the incidence of usage following a report is significantly higher than that preceding a report. This reflects the previously outlined prediction strategy.

<sup>†</sup> Internally, we store and, here, present these emoji as words. It is unclear whether or not users would ascribe the same word with a given emoji. Cf. [http://ceur-ws.org/Vol-997/empire2013\\_paper\\_4.pdf](http://ceur-ws.org/Vol-997/empire2013_paper_4.pdf).

<sup>‡</sup> Relative to the average incident of usage before (or after as appropriate) any affect report; the difference is statistically significant.

## Incidence of Usage Before and After Check-in



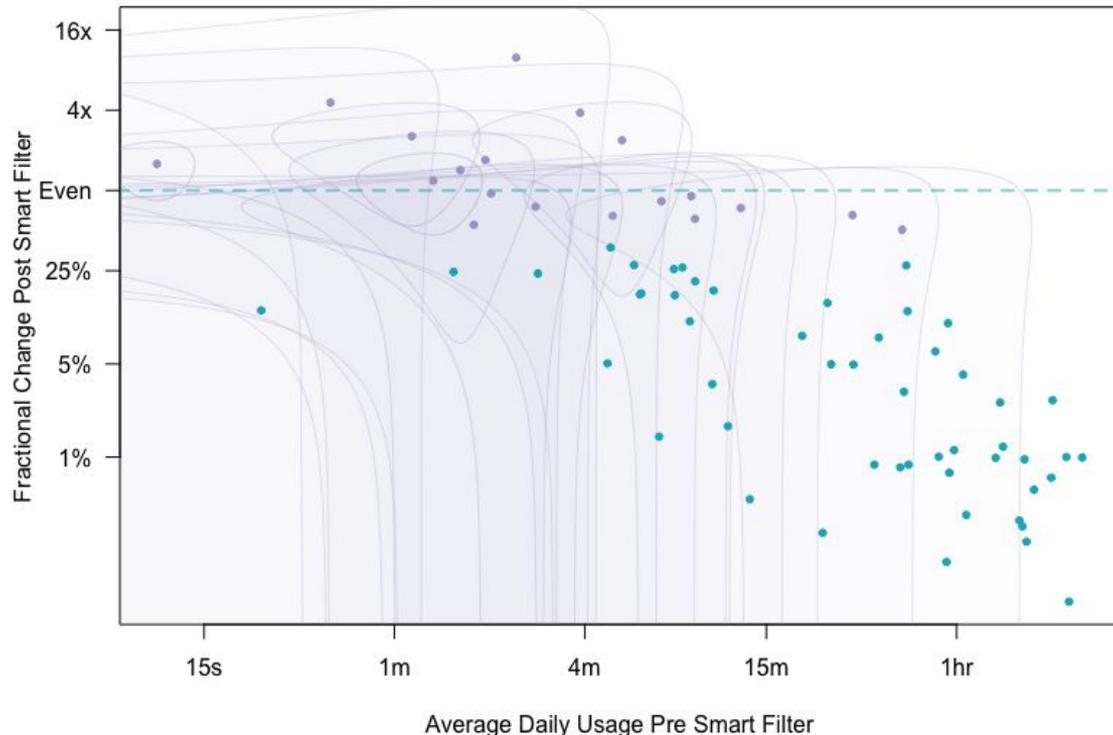
# Onward Reduces Total Time Spent Overusing

With the release of V1.2 and the Smart Filter, we saw a significant reduction in tracked<sup>†</sup> usage for those users with pre- and post-filtering data. **310** users had **3 or more days of data** before and after engaging the filter:

- **183** user dropped their porn usage to zero completely (omitted on a log plot).
- **51** reduced their usage (**teal**).
- **19** had usage statistically consistent with no change (**purple** with 95% CI regions).
- 49 used neither before nor after.
- 8 did not use before filtering but did after.

Onward **arrests or significantly reduces** trackable usage in **89 ± 3%** of porn users<sup>‡</sup>.

## Daily Usage Pre- and Post-Filter



<sup>†</sup> We have not quantified the frequency with which users circumvent tracking and blocking. It is possible users are instead using other devices or are disabling the Onward VPN.

<sup>‡</sup> This neither includes the 49 users who did not use porn pre or post filter nor

# Onward Helps Impulse Control, Reduces Urges

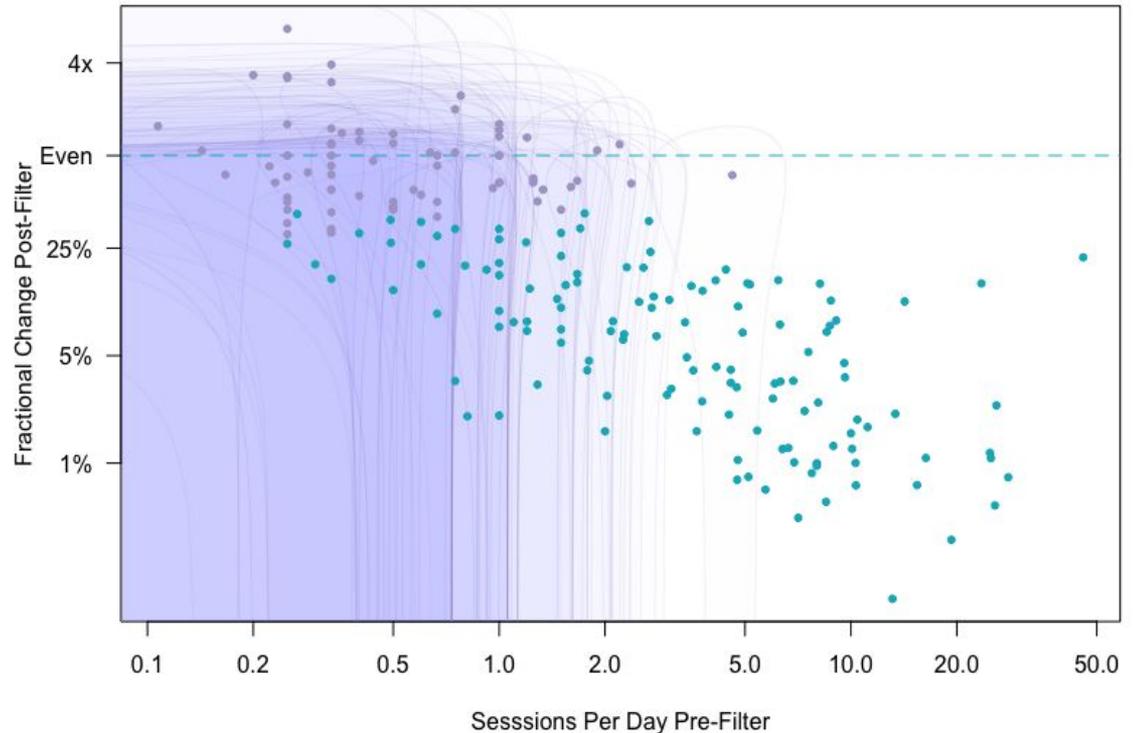
On the same 310 users, we similarly analyze number of attempted sessions (filtered or snoozed). This gives us a sense of users' desire to use and response to impulsive actions.

- 53 user completely arrested their attempts to access porn (omitted)
- 127 reduced their attempts to access porn (teal points).
- 73 had usage statistically consistent with no change (purple with 95% CI regions).
- 18 attempted neither before nor after.
- 39 attempted to use after filtering but not before.

Onward arrests or significantly reduces trackable usage attempts in **62 ± 5%** of porn users<sup>†</sup>.

<sup>†</sup> This neither includes the 18 users who did not attempt to access porn pre or post filter nor accounts for potential statistical variation in the zero attempts ascribed to the groups of 53 or 39 users.

## Attempted Sessions Pre and Post Filter





# ONWARD

Findings, Metrics, and Methodology

Dr. Ken Henisey  
[ken@onward.org](mailto:ken@onward.org)