



Predictive Data Analytics Driving Retention and Revenue

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The Bottom Line

- Our predictive data analytics driven retention strategies have reduced churn by...
 - 35% at 12 months post launch
 - 24% full year 2016 vs. 2015
- These results are on top of the following in the previous 5 years...
 - Daily Individually Paid Audited Circulation – within the top 5 least decline among top 25 to 50 US pubs.
 - Average Revenue per Subscriber – Doubled
- We'll share 4 basic predictive data analytics application case studies driving retention and revenue

Audience Data is helping us better understand; at the **individual customer level...**

- Engagement habits and dynamics
- Relationship quality
- Cancellation probability
- Retention treatment influence
- Conversion propensity
- Monetization opportunities

Predictive Analytics is guiding us

What is Predictive Analytics?

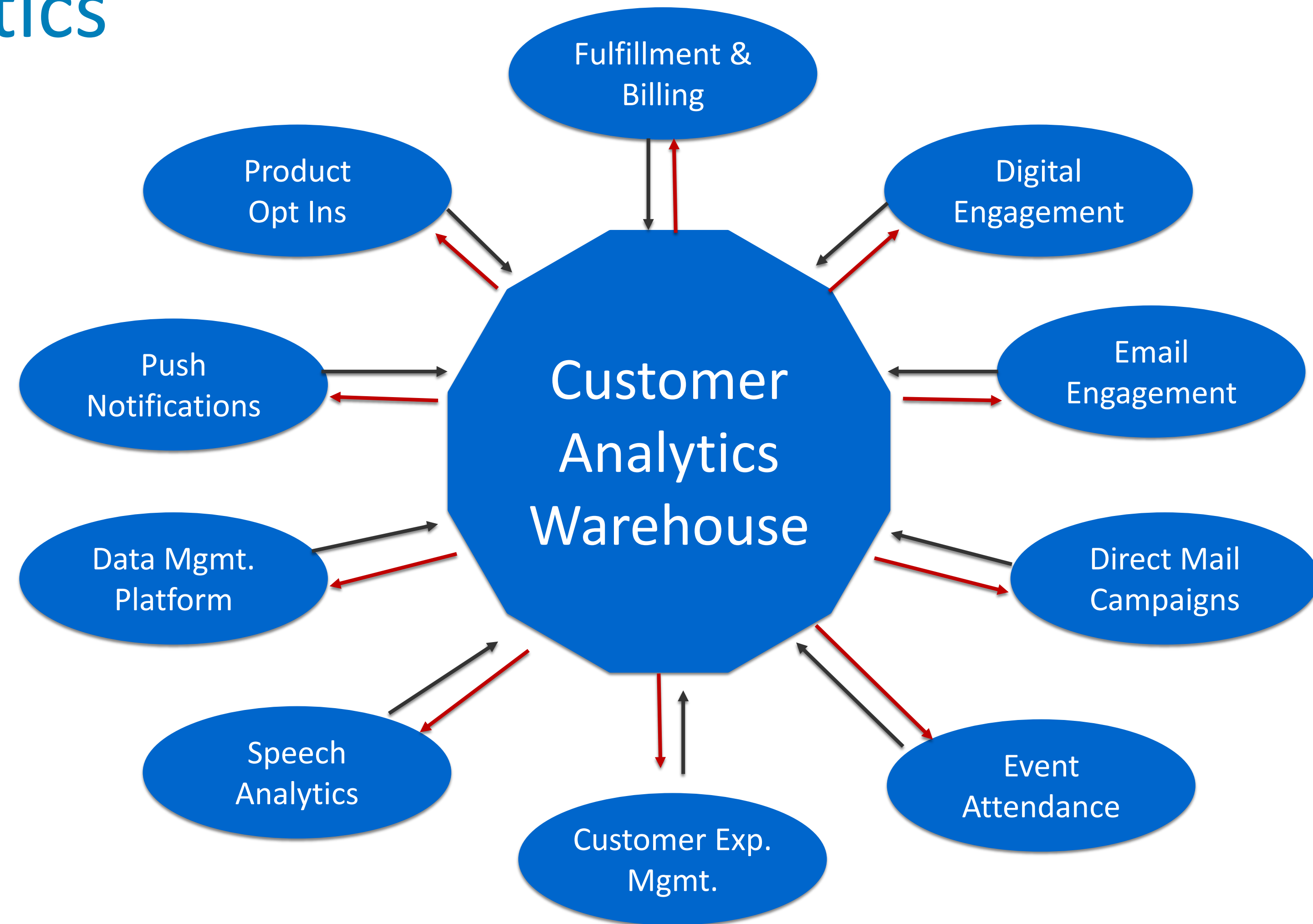
- **Data Science** – mining, statistics, modeling, machine learning
- **Exploits Patterns** – Capturing Relationships
- **Predicted Score** – (probability) for each individual
- **Actions and options** – to benefit from the predictions

Modeling

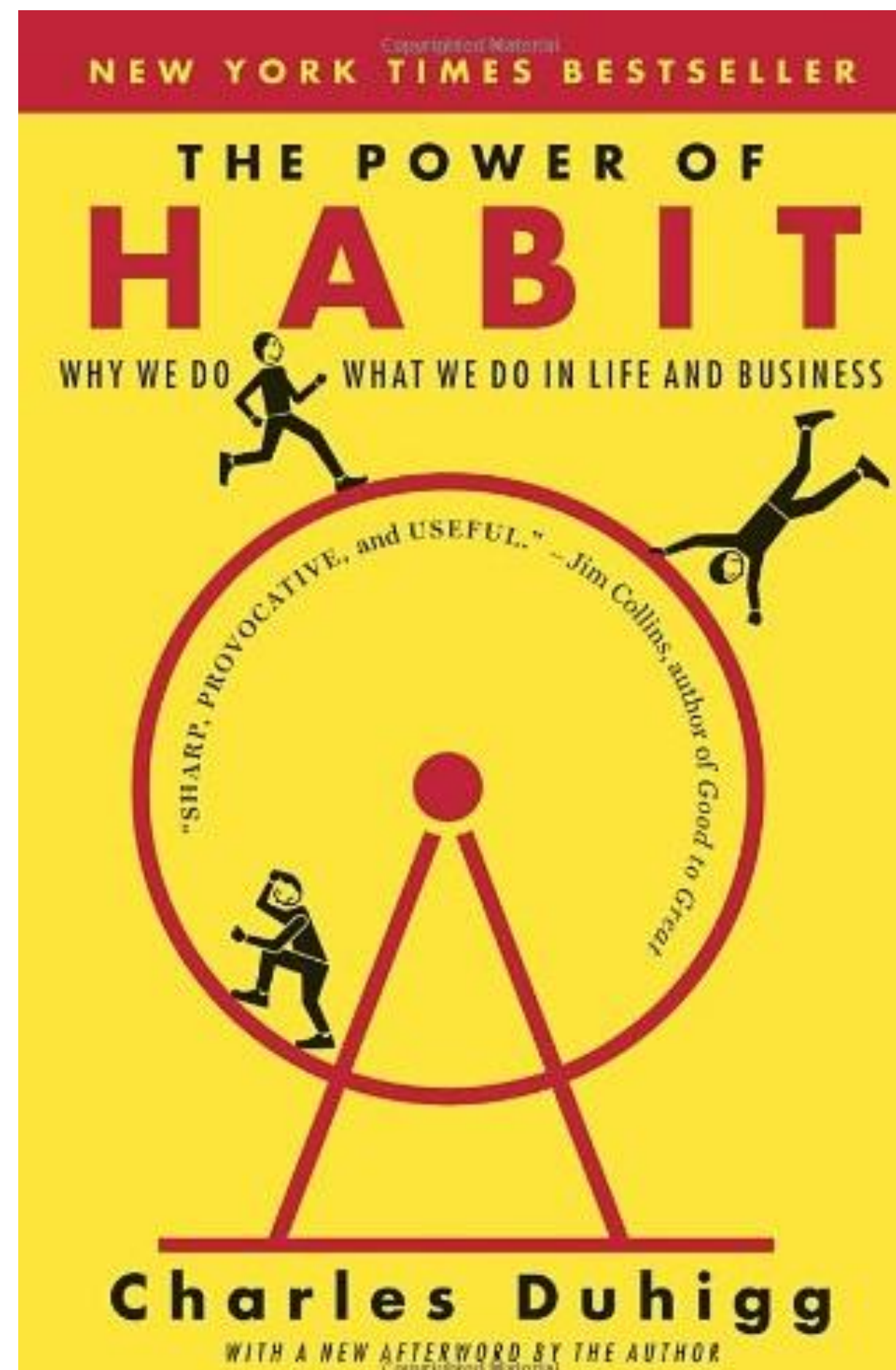
- **Propensity** – likelihood of conversion
- **Churn** – probability of canceling, declining engagement
- **Persuasion** – influence and lift (sure, self-selectors, swing)

Matching and Integrating Customer Records Enables Predictive Analytics

Golden Customer Record



Understanding the Science of Habits Compliments the Leveraging of Predictive Analytics



- Dictionary.com – an acquired behavior pattern regularly followed until it has become almost involuntary
- Charles provides a framework for understanding **how habits work and a guide to experimenting with how they might change**
 - Craving: 4 days/100 hours to break
- Retention Marketing – **start with identifying each individual subscriber's routine of engagement (habits) with your touchpoints and experiment with stimulus when you detect a change in routine**

Audience Data Paradigm Shift

- **Predictive Analytics over “Gut Instinct”** – however, it’s a careful balance between art and science that exploits data analytics and that will drive us forward
- **What is the Impact on Audience Satisfaction, Retention, and Price Elasticity** – needs to be top of mind in strategic decision making across the organization
- **Brand Engagement over Platform Consumption** – it’s all customer touchpoints
- **Customer over Product Perspective & Individualized over One Size Fits All** – marketing and content delivery focused on the individual customer

Four Basic Predictive Analytics Application Case Studies with significant Retention & Revenue Impact

- 1 – Dynamic Messaging for Engagement Deviations
- 2 – Surprise and Delight Retention Marketing
- 3 – Optimizing Surprise and Delight Retention Marketing
- 4 – Determining Niche Product Opt Ins



Application Case Study 1 – Dynamic Messaging for Engagement Deviations – Payments

- Communications triggered by subscribers deviations from prior payment behaviors instead of a generic communications sequence applied to all subscribers
- 13% reduction in formers at 4 months post application for those that deviated

Application Case Study 2 – Surprise & Delight Retention Marketing

- Gift or expression of gratitude sent to subscribers with high or accelerating probability of churn
- Reduction in formers –
 - Gift for high churn probability subscribers: 40% at 5 months; 20% at 9 months
 - Gratitude for accelerating churn probability subscribers: 30% at 5 months; 15% at 9 months



Optimizing Retention Marketing – Net Lift/Persuasion Modeling

- Identifies “swing/persuadable subscribers.” Three groups...
 - Sure – Will behave like you want them to, even if you don’t target them. They are already persuaded.
 - Self Selectors – Likely to do decision on their own. Retention efforts could even have an adverse effect.
 - Swing/Persuadable – Will have a positive response to retention marketing. Need some convincing and open to being convinced.
- Methodology: **Random Forest Learning** (Machine Learning Algorithm)
- Additional \$80k in retention spend **saves 3700 more subscribers**

Net Lift/Persuasion Modeling Insights

Typical Subscriber – Greeting Card Treatment

| Account_num | 23358916 | 43316337 |
|--------------|----------------------|----------------------|
| Net Lift | 7% | -5% |
| pf | 0.73 | 0.04 |
| income | Lowermid | Midscale |
| age | Younger | Older |
| period | 8 | 8 |
| tenure | 0-1 years | 0-1 years |
| source | DIRR | VOLN |
| EZpay | 0 | 1 |
| num_comps | 0 | 9 |
| Payment_days | -4 | -11.8 |
| Tenure days | 177 | 16 |
| freq | Thursday & Sunday | Thursday & Sunday |
| Weekly pay | 2 | 2.5 |
| Billing | NON | NON |
| pf_change | -0.005 | -0.024 |

Subscriber on the right is a typical self-selector

- Started subscribership voluntarily
- 9 complaints in 16 days
- EZpay

Net Lift/Persuasion Modeling Insights

Typical Subscriber – Charger Treatment

| Account_num | 71710988 | 20296878 |
|--------------|-----------|-----------|
| Net Lift | 7% | -4% |
| pf | 0.72 | 0.22 |
| income | Lowermid | Midscale |
| age | Younger | Mature |
| period | 8 | 8 |
| tenure | 0-1 years | 5 + years |
| source | BILL | VOLN |
| EZpay | 0 | 0 |
| num_comps | 0 | 0 |
| Payment_days | 57.33 | -10.42 |
| tendays | 249 | 9581 |
| freq | Other | Daily |
| Weekly pay | 2 | 10.09 |
| Billing | 2nd renew | NON |
| pf_change | -0.005 | 0.0006 |

Subscriber on the left needs stimulus

- Pays bill 57 days post expire on average
- Just received 2nd (reminder) bill
- Very likely to churn (high pf)

Subscriber on the right doesn't want a charger

- Midscale and mature, might already have chargers
- Already well-engaged

Application Case Study 3 – Net Lift/Persuasion Modeling Optimizing Surprise and Delight

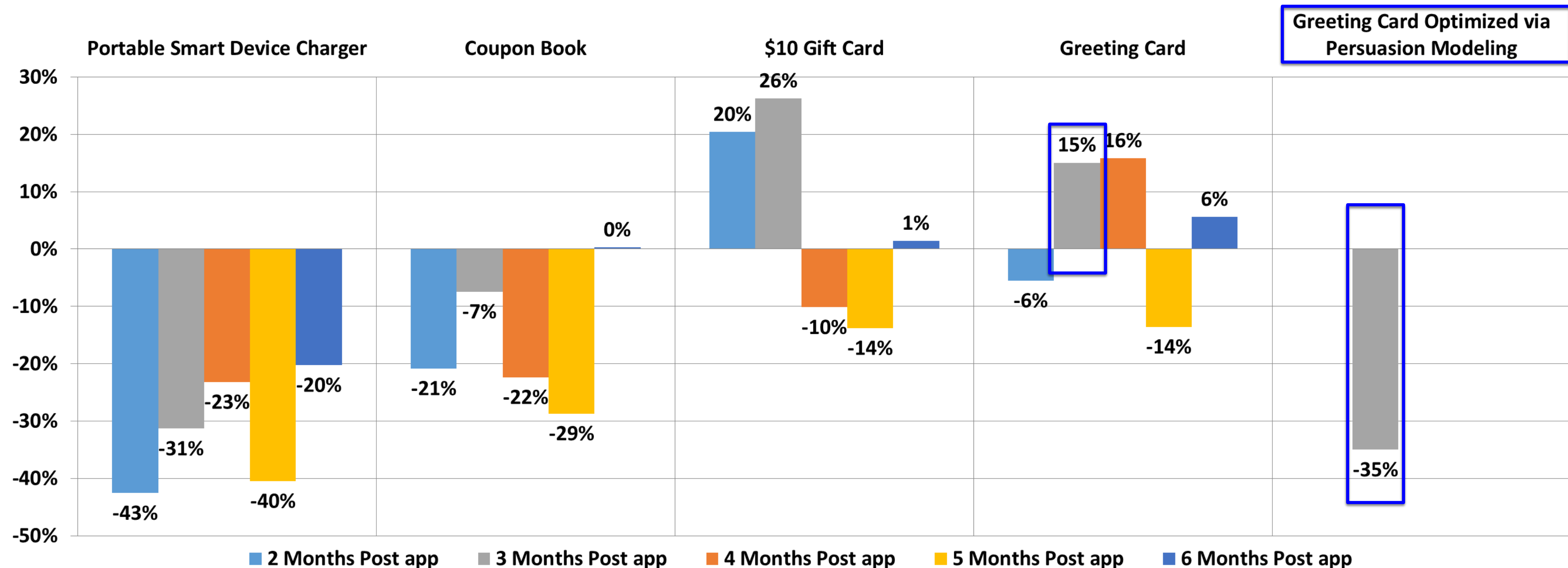
Target **all swing clients** with Net Lift Score >2%, with most suitable treatment optimizing cost per save

| | Base case (based on churn level) | | | | | Net Lift/Persuasion Model | | | | | | |
|----------------------------|----------------------------------|-----------|----------|------------------|--|---------------------------|-----------|-------------|-----------|------------------|--|-----------------|
| | Accelerating | High | Low | Sum | | Group 1 | Group 2 | Group 3 | Group 4 | Sum | | Variance |
| Treatment | Greeting | Charger | Greeting | | | Greeting | Charger | Coupon Book | Gift Card | | | |
| Population | 4,395 | 11,165 | 44,907 | 60,467 | | 113,091 | 9,579 | 4,702 | 3,835 | 131,207 | | |
| | | | | | | | | | | | | |
| % Formers 90 Days Post App | | | | | | | | | | | | |
| Treatment | 6.8% | 4.8% | 3.6% | | | 2.8% | 2.9% | 4.0% | 3.1% | | | |
| Control | 9.7% | 6.9% | 4.1% | | | 6.1% | 6.0% | 7.6% | 6.3% | | | |
| Net Lift ppt | 2.9% | 2.1% | 0.5% | | | 3.3% | 3.1% | 3.6% | 3.2% | | | |
| Net Lift % | 42.6% | 43.8% | 13.9% | | | 117.9% | 106.9% | 90.0% | 103.2% | | | |
| | | | | | | | | | | | | |
| Expense | | | | | | | | | | | | |
| Unit | \$0.55 | \$16 | \$0.55 | | | \$0.55 | \$16 | \$7 | \$8.50 | | | |
| Total | \$2,417 | \$178,640 | \$24,699 | \$205,756 | | \$62,200 | \$153,264 | \$32,914 | \$32,598 | \$280,976 | | \$75,219 |
| Subs Saved | 127 | 234 | 235 | 596 | | 3743 | 296 | 172 | 123 | 4334 | | 3738 |
| Per Save | \$19 | \$763 | \$105 | \$345 | | \$17 | \$518 | \$191 | \$265 | \$65 | | (\$280) |

Results: Our net lift model defined that an additional \$75k saves 3700 more subscribers

Application Case Study 3 – Net Lift/Persuasion Modeling Results

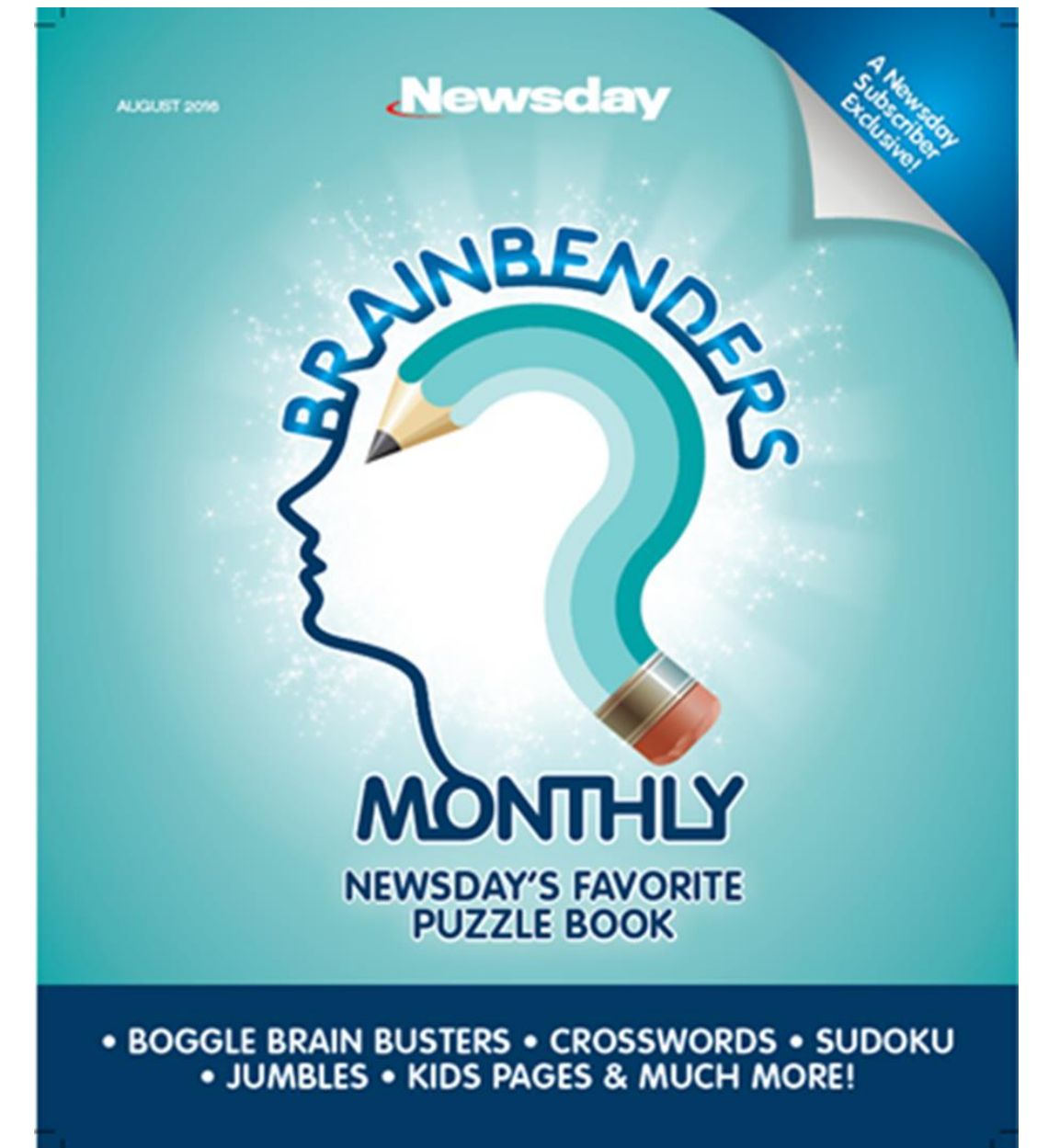
Suprise & Delight Retention Marketing - Formers Test vs. Control: Subs with High Churn Scores



Results: Reduction in formers via gratitude to high churn subs is 35% at 3 months vs. -15% prior to persuasion model

Application Case Study 4 – Determining Niche Product Opt Ins

- Providing additional products/content, as identified by consumer feedback coupled with churn modeling, on a **no charge opt in basics**
- Brain Benders Monthly
 - 12% reduction in churn probability upon opting in
 - 5% more price increase with nearly no stops
 - 50% reduction in churn at 4 months post opt in



What's the Total Impact
on Churn?

Impact on Churn – Trailing 12 Months Year/Year

