Unresponsive Customers: Acquisition, Retargeting and Win-Back

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ABSTRACT

With firms losing an average of 25% of their customer base every year, understanding and engaging unresponsive customers has become more critical than ever. We characterize unresponsive customers as either prospects that have never purchased from a firm, or former customers that have not purchased in at least twelve months. Since 55% of all communication is non-verbal, how can online firms cut through the silence and engage these unresponsive customers *digitally*?

Our paper is an exploration into the three current management strategies firms implement to reach the unresponsive customer: acquisition, retargeting, and win-back. Included is an examination into recent technological advancements that provide a new layer of visibility into the behavior and emotion of the unresponsive customer. We also discuss how Emotional Value, which is described as the economic worth of feelings, can be implemented to more effectively win-back customers.

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1. Introduction

The inspiration for writing this thesis started on a plane ride from Boston to Veracruz, Mexico. We were speaking at an innovation conference the following day in front of several thousand engineering undergraduate students in the village town of Misantla. The main discussion on our plane ride revolved around the concept of 'likability.' Upon landing, we scoured the Internet for any science-based material we could find on the topic. Unfortunately, there was not much to be found.

The following week back in Kendall Square, Abraham seemed a bit upset. After further inquiry, it turned out that he had a terrible experience while receiving a haircut at a prominent Boston salon. From the moment Abraham stepped into the salon, the front desk receptionist was incredibly rude. Even though Abraham's haircut was satisfactory, the initial bad service experience meant he would never go back to that salon. Essentially, 30 seconds of a bad attitude had just lost this salon not only a loyal client in Abraham, but the future business of his wife and any friends that he or she would no longer recommend. Assuming the haircut costs $100 and Abraham and his wife get monthly haircuts, this translates to a $2,400 annual loss. Over the course of that busy Saturday, this receptionist may have treated another 30 clients in a similarly rude fashion, which could have easily translated in a loss of over $70,000 for the salon that year.

This salon experience served to increase our intrigue in the immense power of likability. We wanted to find as many research papers and empirical data points as possible on the topic, but our search came up more or less empty. Finally, we found a book called 'Emotional Value.' The authors defined emotional value as the "economic value or monetary worth of feelings when customers positively experience an organization's product and/or services." The book goes on to clearly outline how emotional value, as much as quality or any other dimension of an organization's worth, can make or break a business (Barlow & Maul, 2000).

The following week, during a negotiations seminar run by MIT Professor Jared Curhan, we were struck by the concept of 'Subjective Value.' Professor Curhan describes 'Subjective Value' as the "social, perceptual, and emotional consequences of a negotiation." In Professor Curhan's paper 'Objective Value of Subjective Value," he argued that, over time, subjective value will predict higher future objective value. Because behavior is driven largely by how people feel, Curhan proved that if you make an initial negotiation pleasant and leave your counterpart with good feelings about the interaction, you will extract more objective value not only in the initial negotiation, but also in subsequent negotiations (Curhan, Elfenbein, & Eisenkraft, 2010).

Reading through the concept of 'Emotional Value' and 'Subjective Value,' we felt as though the topic of likability had been researched and validated. But as described in the readings, one of the central factors in generating emotional value revolved around the practice of hiring empathetic employees. The point was that empathetic employees were more capable of reading customer emotions. This innate ability to read emotions allows employees to better interpret a customer's true needs, and provide a superior experience. For instance, if an employee at a wine store notices a customer casually browsing various selections of Merlot, an empathetic employee will take that as a cue to offer additional insights about the best vintages. Conversely, if that same employee notices a customer barge into the store, looking anxiously at their watch, the employee takes that as cue to swiftly assist that customer (Barlow & Maul, 2000). However, since 55% of all human communication is non-verbal (Kurien, 2010), we wondered how digitally native businesses could bridge this non-verbal gap, and create emotional value *digitally*?

This idea of digital likability pushed us to explore the ways in which consumers express their feelings digitally. We found a research paper that detailed how a group of researchers analyzed the emotional content of thousands of online product reviews using Natural Language Processing (NLP) methods (Ullah, Amblee, Kim, & Lee, 2016). While reading through the paper we stumbled upon an assumption that completely startled us. As described in the paper "*however, a key problem with analyzing the volume and valence of word-of-mouth to understand consumer's word-of-mouth behavior is the under-reporting bias, whereby only those consumers who are extremely satisfied or extremely dissatisfied write reviews, while those consumers who felt that the product was "just okay" may not be motivated to post a review*" (Ullah et al., 2016). Essentially, the researchers assumed that a consumer was indifferent to a product if they didn't write an online review about it.

In thinking back to Abraham's awful service experience with the salon, although he was not planning to write a negative online review, he was certainly upset with the service. Unless the salon personally apologized, and presented an offer to compensate Abraham for the bad experience, he would never come back.

But how was the salon owner to know his customer felt since he never decided to post a review? With the recent innovations in technology (Krawczyk-Sokołowska & Ziołkowska, 2013), could there ever be a way for this salon to know how Abraham truly felt without having to ask him? Since Abraham would never step into that salon for a haircut ever again, was there a way for them to create emotional value through digital communications? These were the questions we aimed to explore in our thesis research.

The next several sections of this paper describe how firms implement and manage certain strategies to deal with unresponsive customers like Abraham. The three strategies we will describe are: acquisition, retargeting, and re - engagement (treated in this paper as win-back). Each of these strategies relate to different stages of the unresponsive customer. Since Information and Communication Technologies (ICT) advancements provide new layers of visibility into customers' behaviors and emotions (Peterson & Merino, 2003), we will cover the initial implications of particular technologies within the three strategies. Finally, we will discuss and illustrate how firms currently implement and manage acquisition, retargeting, and win-back strategies – in order to facilitate the understanding of their unresponsive customer segments.

2. The Unresponsive Customer

We characterize unresponsive customers as belonging to one of three segments. First, there are prospects that may be valuable future customers once they are exposed to messaging about the product and/or service. These prospects are the focus of acquisition management. Second, we have prospective customers that, at some point, visited the firm's website but are yet to purchase. These prospective customers are the focus of retargeting management. Finally, former customers that have purchased at least once in the past, but have not purchased in at least twelve months. These former customers are considered "lost" and are the focus of win-back management.

Since firms do not have the luxury of face-to-face interactions with these unresponsive customers (Kuan, Bock, & Lee, 2007), we will explore how they can better understand them, and discuss which options are available to acquire or reacquire them. For the purposes of this paper we define acquisition as a purchase of a firm's product/and or service. In the following section, we dive a little deeper into the concepts of acquisition, retargeting, and win-back.

2.1 Acquisition Management

Every year, according to (Ang & Buttle, 2006), the average firm loses 25% of its customer base, making the need to acquire new customers crucial for any business. Additionally, these authors found that a firm with a 16.7% share of market enjoys 5 times the revenue impact from a 1% increase in acquisition than from a 1% increase in retention.

When firms engage in customer acquisition management, there are three major issues to consider: which potential customers to target, how to communicate with them, and what to offer them (Ang & Buttle, 2006). (Blattberg, Malthouse, & Neslin, 2009) emphasized that most companies are unselective in their customer acquisition processes, meaning they fail to adequately target their acquisition activities. Being able to more accurately identify a firm's most profitable customers has led to the mass adoption of the concept of customer lifetime value (CLV) (Hardie et al., 2006). CLV is defined as the present value of future cash flows associated with a customer (Borle, Singh, & Jain, 2008). In general, the CLV framework measures how changes in customer behavior could influence customers' future profits, or their profitability to the firm. Typically CLV calculations assume a 3 to 4 year customer lifecycle (Estrella-Ramon, Swinnen, Vanhoof, & Sanchez-Perez, 2013).

Starting with the notion that the past dictates the future, there are two different models of CLV: (i) historical and (ii) predictive. While historical models only look at previous transaction history, predictive models discover what will happen in the future under similar conditions (Estrella-Ramon et al., 2013). With the constant technological innovations described in an upcoming section, this predictive CLV modeling can perhaps be taken to the next level.

2.2 Retargeting Management

When a customer has interacted with a firm's website, but is yet to purchase, we consider them unresponsive (Chiu, Lin, Sun, & Hsu, 2009). Innovations in the parsing and processing of individual level browsing data now enable firms to offer product recommendations in real time to consumers who return to their website (Reibstein, 2002). If these prospective customers still don't purchase and leave the firm's website, technology has enabled firms to reach out to these customers using dynamic retargeted ads featuring pictures of the exact products they were browsing on the website (Lambrecht & Tucker, 2013). Conceptually, the strategy of offering highly personalized and relevant messaging is immensely valuable for the consumer as well as the firm. As a new technology, retargeting was a runaway success. Personalized retargeted ads were six times more effective than standard banner ads (Lambrecht & Tucker, 2013).

Adroll, a retargeting start-up company, realized that retargeting could bring back 98% of customers who otherwise would never return to a firm's website. The company not only displayed ads for products the consumer had already engaged with, but also displayed ads the consumer had never seen, but could potentially be interested in (Konrad, 2014). In 2008, Adroll had revenues of $111,000, and by 2012 the start-up had annual sales of $50 million (Konrad, 2014). Through a strategic partnership with Facebook, Adroll allowed its clients to utilize retargeting via Facebook ads, which created a 1,600% return on their clients' investment (Finkle & Finkle, 2013).

Despite the unprecedented success of companies like Adroll, (Lambrecht & Tucker, 2013) found that dynamically retargeted ads are often not as effective as generic retargeted ads of the same brand. The research suggested that the effectiveness of a retargeted ad depended on whether the concreteness of the message matched how narrowly consumers construed their preferences. For example, a consumer who is looking for a "beach vacation" has a broad, high-level goal, not a narrowly construed preference such as "vacation in Costa Rica with access to an olympic sized pool." In the case of the consumer with the high-level goal, a generic retargeted banner ad with beach and ocean images was more effective. Additionally, the research suggested that dynamic retargeting is most effective when managers have access to external browsing data, which would help them identify when a consumer had evolved from a high-level goal to a narrowly construed goal (Lambrecht & Tucker, 2013).

2.3 Win-Back Management

Despite the best acquisition and retention efforts, customers still defect (Borle et al., 2008). We spoke with digital marketers across hotels, e-commerce sites, and mobile web applications that agreed that once a defected customer has not made a purchase or engaged with the firm's communication in 12 months, they were effectively considered "lost." The firms we spoke with also typically offered between 6-8 "win-back" communications spread throughout the year of defection (Kumar & Bhagwat, 2015). While it may prove difficult to reacquire these unresponsive customers, research suggests that if they can win them back, they may be more profitable in their second-lifetime than their first-lifetime.

(Kumar & Bhagwat, 2015) conducted a large-scale field experiment with a U.S.-based telecommunications products and services firm. The data tracked the activities of the firm's customers over seven years (2006 to 2014), three years before defection and four years after reacquisition. The team also tracked the reason for defection, and the length of time that the customers were lost. A one-time win-back offer was delivered to 53,729 defected customers in the two to six-month window since their defection.

So what happened? Of the 53,729 lost customers, 14,384 – equivalent to 27%, were reacquired. The conclusion of the study revealed several key insights about regaining lost customers.

First, the probability of reacquisition was impacted based on first-lifetime referral and complaint activity. The higher volume and valence of referrals led to a higher probability of reacquisition. Interestingly, if the firm attempted to address a complaint of lost customer they had a higher probability of returning. Whether the complaint was actually addressed appropriately was less important than the attempt. By listening to customer complaints, and working to solve the issues, the firm was successful in building a relationship.

Second, if the defected customer left for service related reasons, they were more difficult to win-back. Conversely, if a customer defected for price related reasons, they were easier to win-back but were more likely to defect again. This makes sense, as people won-back with a discount may be price-seekers who are less likely to exhibit the characteristics of a loyal customer (Tokman, Davis, & Lemon, 2007). Loyal customer characteristics include: (i) making regular purchases, (ii) purchasing across product and service lines, (iii) referring others, (iv) demonstrating an immunity to the pull of competition, (v) tolerating an occasional lapse in the firm's support without defecting (Griffin & Lowenstein, 2001)

Finally, within win-back offers, customers who were won-back with price-related reasons had the longest second-lifetime duration. While customers who were won-back for service-related reasons had the highest second-lifetime profitability (Pick, Thomas, Tillmanns, & Krafft, 2015). Unexpectedly, lost customers who were offered a bundled win-back offer (both service and price) had the lowest second-lifetime duration of all. These results imply that people who left for service-related reasons seemed to be more invested in their relationship with the firm, and took their second-lifetime with the firm more seriously. Also, regained customers may have seen the "too attractive" offer as inauthentic and felt more entitled to take advantage and defect again (Kumar & Bhagwat, 2015).

The above findings also suggest the power of emotional value is at play. First, the act of *attempting* to handle a complaint was enough to win-back customers. This attempt from the firm demonstrates that they were listening to the customer, which made a powerful impression. Second, people who defected for service reasons were more profitable in their second lifetime. These former customers place quality and level of service over price, and are more likely to want to build a lasting relationship. Finally, win-back offers that were "too attractive" and perceived as inauthentic did poorly in comparison to targeted offers. The "too good to be true" offers may have made former customers feel like the firm did not listen to their specific concerns, which decreased the potential to re-establish an authentic connection.

The following section provides an exploration of our research on key elements of Information and Communication Technologies that could potentially augment the impact of unresponsive customer strategies (Nettleton, 2014). In order to understand how technology might influence the three strategies, we felt it was important to first discuss the origins of our recently developed data driven culture.

3. Technological exploration

Since the invention of the telegraph in 1774, humanity has deeply immersed itself in exploring mechanisms of communication unconstrained by physical location. However, the pace has not always been agile. It took 65 years to actually launch the first telegraph service in 1839. The success of telegraph technology sparked a revolution in human communication, including: the telephone in 1871, the first radio transmission in 1900, local television broadcasts in 1928, the inception of computer theory in 1936, and expansive access to the internet and the world wide web in 1990. This revolution has now positioned firms to explore specific technologies that aim to improve its connections with customers.

With the present day convergence of devices such as telephone, computer, television and radio in one "smarter" device, it is perhaps more crucial than ever to communicate the right message at the right time and context.

Further, beyond choosing the most suitable communication channel for the desired message, defining and designing the actual content that a firms' customer's would potentially consume is imperative. When content is structured in a way that is personalized to the consumer, even the most stubborn opponents of an idea can be persuaded.

We live in a data-driven era (Pentland, 2013). Within their daily operations, firms can radically transform the scope and depth of their data streams. Consider the millions of daily transactions happening every day in major retail stores in any megacity. These retail stores all have automated systems in the form of computer software; which in the case of customer data refers to the Customer Relationship Management (CRM) enterprise software (Li & Zhang, 2006). In order to not only collect, but also create meaningful insights from this customer data, methods for dissecting and analyzing the data are required.

As access to customers' data becomes more accessible and plentiful, opportunities for exploring and exploiting this data increase proportionally. As (James, Witten, Hastie, & Tibishirani, 2013) suggests, the expansion of "big data" across multiple industries has increased the managerial relevance of statistics, particularly in the domain of Statistical Learning. Statistical Learning is defined as the set of tools for modeling, and subsequently understanding more complex sets of data. More complexities also create more possibilities. Managers can securely attempt to create predictive models that use customers' data precisely to leverage the accuracy of the 3 strategies: acquisition, retargeting and win-back. Firms can use these predictive models or predictive data analytics to produce a glimpse into the future. The use of predictive technology can be a major advantage for firms to create, extract, and deliver more value from its customers.

(Kelleher, Mac Namee, & D'arcy, 2015) define *Predictive Data Analytics* as the "art of building and using models that make predictions based on patterns extracted from historical data." The authors offered contextual examples of the real-life applications of their field of knowledge and research, such as medical diagnosis and dosage prediction, risk assessment, pricing strategies, propensity modeling – as the prediction of the likelihood, or propensity, of individual customers to take different actions and document classifications. While their examples have the word 'prediction' in common, (Kelleher et al., 2015) did mention the distinction that in some cases this concept does not imply the conventional temporal aspect (i.e. predicting the choice of literature in an electronic commerce website). They also introduced the applicability of machine learning, as the automated process that extracts patterns from data into training models to make predictions based on a set of historical examples.

(Alpaydın, 2014) went beyond the big data construct, and expanded the continuous growth of the theory to process data and turn it into knowledge. (Alpaydın, 2014) defined machine learning as "programming computers to optimize a performance criterion using example data or past experience, using the theory of statistics in building mathematical models that may be predictive (targeted on making predictions from data) or descriptive (focused on gaining knowledge from data), since the core task at hand is creating inferences from a sample." Therefore, technologically enabled multi-dimensional multi-variable analysis is feasible and, more importantly, actionable.

3.1 Technologies supporting customer acquisition

The one factor that every successful business has in common is that customers make purchases. In order to continually acquire customers, firms must be aware of acquisition costs. Having a proper budgeting process for allocating the necessary expenses for customer acquisition activities is related to excellence in customer acquisition (Ang & Buttle, 2006). The "rule" introduced by the authors is that the lifetime value of each customer should exceed the costs of that customer´s acquisition. But, how are digitally native firms handling their customer acquisition initiatives?

Startup companies such as Instagram and Pinterest have mastered the "art" of customer acquisition by focusing on building a community over monetization (Heffernan, 2013) (Zarro & Hall, 2012). These two social media giants also implemented superior User Experience (UX) techniques to create an outstanding sign-up process (Miller, Chang, & Terveen, 2015).

In the case of Pinterest, their web pages are designed to create a sense of belonging that translates into a strong emotional connection with its online users (Mittal, Gupta, Dewan, & Kumaraguru, 2013).

In contrast with the traditional outbound marketing method that "pushes" the product and/or service to a wide array of potential customers, modern technologies enable on inbound marketing method that "pulls" a targeted customers segment into the content that may influence his decision of opting into a specific service or buying a particular product. This "pull" methodology most commonly manifests itself in email campaigns, relevant online content, and search engine optimization. Technology allows marketers to gain visibility into who engages with their content, enabling firms understand who their customers are and what they value most.

3.2 Technologies supporting customer retargeting

Retargeting is considered the evolution of online advertising. (Berke, Fulton, & Vaccarello, 2014) described how a more sophisticated marketing method of retargeting web cookies – small pieces of code embedded in a digital communication, such as an email or an online landing page. The web cookies allow any firm with an online presence to observe the behavior of potential customers that navigate its digital assets (i.e. selecting an item in the e-commerce section, and placing it in a wish list).

In order to assess the value of each prospective customer, Retargeting works in concert with real-time bidding of online ads. The real-time factor is the very essence of the value delivered by retargeting, since it allows the analysis of each customer´s value to the firm in a particular time and context. Before retargeting, an advertiser purchased online ads by a publisher (Goldfarb & Tucker, 2011). The transaction specified a volume of impressions (of the ad displayed on a web site) and a price-per-1000 ad impressions. This model is presented by (Berke et al., 2014) as contextual targeting, following the premise that the ads shown on a web site are contextually relevant to a particular segment of customers.

However, the future of retargeting has challenges, particularly in the expansion of the multi-device usage of customers. If today a prospective customer embarks on a quest for a new smartphone, the initial search might be performed in the actual smartphone of the potential customer. Later on in the day, that same user might decide to browse reviews of that same smartphone, using his laptop. The subsequent day, that customer might make the actual purchase in a brick-and-mortar store located near his office. This migration among devices, each one with diverse standards and policies, and the physical world, tend to generate more complexity when analyzing customer´s behavior.

Several digital firms offer retargeting services that work as turnkey solutions for this marketing technique, such as Google, ReTargeter, Triggit, Perfect Audience and the widely popular, AdRoll (Finkle, 2013).

3.3 Technologies supporting customer win-back

Given the continually rising rate of defected customers, churn prevention is a popular topic among firms and academia (Singh & Samalia, 2014) (Neslin, Gupta, Kamakura, Lu, & Mason, 2006). However, winning back customers who haven't purchased in twelve months or longer is a specific niche challenge that seems to receive little attention. In order to begin to win-back these lost customers, firms must understand answer two questions: why did they defect, and which offers are now most relevant to them?

Unfortunately, as former customers go longer without repurchasing, it becomes harder for firms to facilitate communication and understand why they left (Hoffman, Novak, & Peralta, 1999). With the development of advanced statistics, firms are able to run tests with various offers to targeted segments of their unresponsive customers (Tokman et al., 2007). These tests are better known as experiments. The advancement of analytics tools allows these experiments to be measured in real-time, and to provide actionable insights.

Additionally, the search and study of causal effects regarding unresponsiveness should also be a priority. By understanding the circumstance of a lost customer, firms can be more targeted regarding which pieces of content to deliver. The ability to serve relevant content is crucial for any win-back strategy. With unprecedented access to publicly available data, firms can now use predictive models to start answering the question of context. Moreover, the history collected within the firm´s Customer Relationship Management (CRM) technology (Wang & Feng, 2012), might serve as a baseline for understanding and winning back unresponsive customers.

4. Management Example: High-End Hotel Chain

We will walk through examples of acquisition, re-targeting, and win-back strategies through the lens of a high-end hotel chain. Our assumption is that this hotel chain has access to the most comprehensive customer relationship management tools, and uses data from those tools to drive decisions. The numbers and scenarios are fictional, but will help highlight the challenges and opportunities management teams face when dealing with unresponsive customers.

4.1 The High-End Hotel Industry

Due to a steady rise in commissions from OTA's (online travel agencies), as well as increased pressure from online marketplaces like Airbnb (Guttentag, 2013), management within the high-end hotel industry needs to constantly find cost-effective ways to increase revenue and lower costs. A 2014 white paper commissioned by The Hospitality Asset Managers Association revealed that customer acquisition costs have risen 23% (KalibriLabs, 2014). Meanwhile, in New York City alone, the local demand for Airbnb is at nearly 8% of rooms-revenue capture, representing a direct loss to the hotel industry of $451 million from September 2014 to August 2015. These numbers are only expected to increase over the course of the next several years.

4.2 Acquisition Management Sample Strategy

In order to create an effective discussion regarding new customer acquisition, hotel management clearly defines which customers to target, how to communicate with them, and what to offer them (Ang & Buttle, 2006). Secondly, the firm looks back at purchasing histories of new and existing customers within the target segment to verify that they are high-value. Finally, the team calculates customer-lifetime value (CLV) in order to ensure that the cost of acquisition will not be more costly than the cost of retaining the customer.

After running a new customer analysis (Appendix 1), customer revenue analysis (Appendix 2), and a recency of purchase analysis (Appendix 3), the hotel chain determines that the highest value segment is what they have defined as the *millennial business traveler*. This segment is a 25 to 34-year-old that books at least 30 nights per year with the hotel. Also, beyond business travel, the customer likes to book their vacations less than one week before departure, and is most active with the hotel's social channels. The issue in the past with this segment has been the relatively high churn rate, and unpredictability of purchasing habits (Eng, 2016).

Now with the target customer defined, the hotel runs a customer-lifetime value analysis (Appendix 4), and finds that the *millennial business traveler* has a CLV of $10,500. All customer acquisition efforts must fall below this number. Unfortunately, CLV calculations are far from a perfect science. Just because a customer was high-value in the past, does not make it a certainty in the future (Griffin & Lowenstein, 2001).

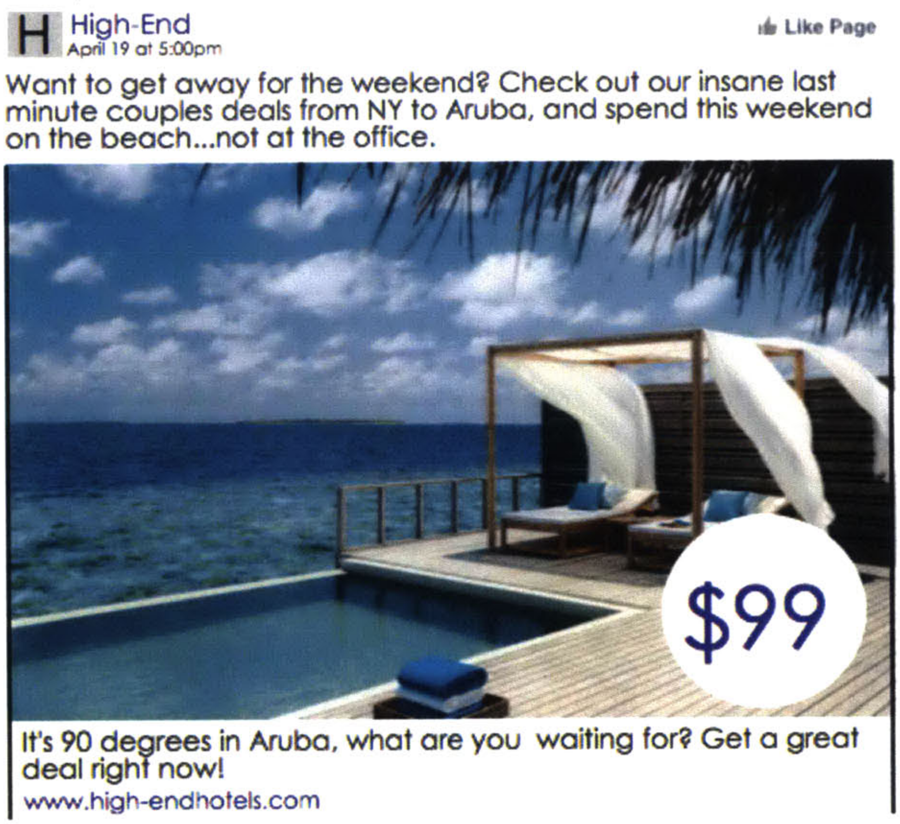
Through previous acquisition efforts, the hotel knows what this segment prefers: highly personalized messaging and experiences, booking rooms with their mobile phones, and accessing critical information via their social channels (Malthouse, Haenlein, Skiera, Wege, & Zhang, 2013).

Figure 1 illustrates how the hotel could potentially implement an advertisement targeted at a new customer via Facebook. As a Facebook advertiser, the hotel can target a user based on location, age, relationship status, interests, languages, and type of work. In our example, the hotel has targeted a user who lives in New York City, works in investment banking, and has a significant other (Facebook, 2010).

Since the targeted ads run on Facebook's platform, the hotel has ample opportunities to test several different messages aimed at the same customer profile. The hotel is able to quickly observe the impressions, cost per 1,000 impressions, the average number of times an individual viewed the ad (Barreto, 2013), the percentage of people saw the ad and clicked through, the number of bookings, and cost per booking.

By continually testing several versions of the ad, hotels are able to learn which ads are most effective at acquiring new customers (Malhotra, Kubowicz Malhotra, & See, 2013).

Figure 1: Targeted Facebook Ad



4.2 Retargeting Management Sample Strategy

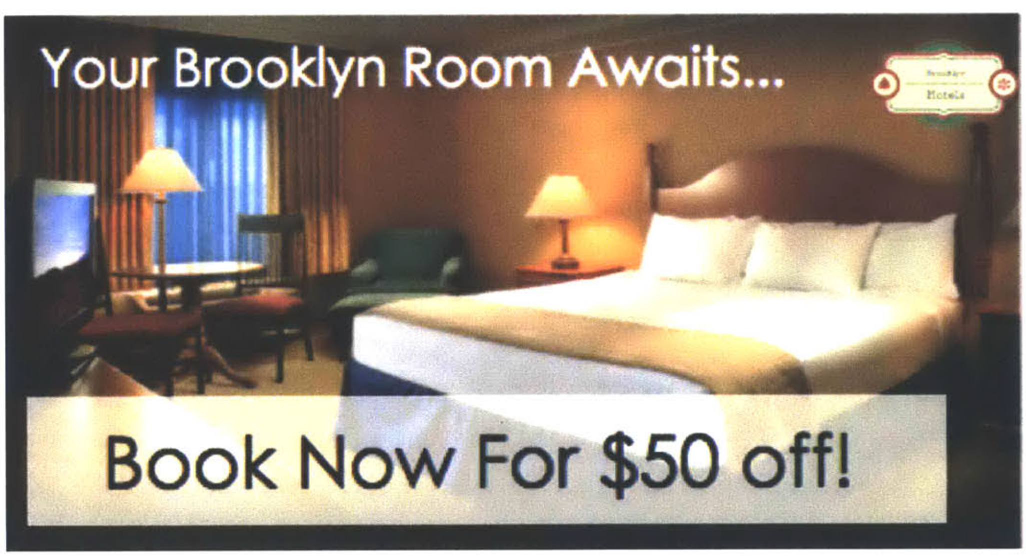
The hotel chain has a contract with a large ad network that works on the firm's behalf to serve retargeted banner ads. Once a consumer who matches the *millennial business traveler's* profile browses through the hotel's website, a pixel tag (1x1 image) is downloaded automatically. This pixel tag records the consumers browsing activity, specifically tracking which locations and types of rooms the consumer searched through. At this point, the ad network integrates this browsing history as part of that consumer's profile.

Later on, when the target consumer browses other websites, he eventually reaches a website whose ads are supplied by the ad network. Since the consumer browsed specific rooms in the New York City location for specific dates, the ad network knows to serve a dynamically retargeted ad with a picture of the exact room the consumer was browsing earlier. If the consumer makes a booking from that retargeted ad, the ad network records the purchase and attributes all ads associated with the conversion. If the target consumer does not engage with the ad, he may have a broad high-level goal of visiting New York City. In this case, the hotel may try generic retargeted ads with images of New York City landmarks (Lambrecht & Tucker, 2013). Figure 2 below illustrates a sample users browsing activity on the hotels website. And Figure 3 represents a dynamically retargeted ad based on that behavior.

Much like the acquisition example, the hotel is able to efficiently run tests to gauge the effectiveness of their retargeting campaign. The hotel is able to observe the cost per thousand impressions, the click-through rate, the cost per click, the cost per acquisition, and perhaps most importantly, the number of assisted conversions. Assisted conversions are events when a user clicks or views a retargeted ad, but then later on views an ad from another campaign and converts (Ratliff & Rubinfeld, 2010).

Figure 2: User browses a specific hotel room on the firm's website

Figure 3: Dynamically retargeted ad by the hotel



4.3 Win-Back Management Sample Strategy

The defection analysis of *millennial business travelers* (Appendix 5) shows that just last year 1,320 customers in that segment defected, representing a loss of $27 million. This is a perfect opportunity for the hotel chain to regain lost high-value customers. In order to manage a successful win-back strategy, the team must first grade lost customers in the target segment by second-lifetime value (SLV). SLV measures the value of a relationship once a customer is won-back and can be influenced by factors such as reason for defection, first-lifetime referral complaint history. The hotels SLV analysis (Appendix 6) shows that a successful reacquisition can be more than double as profitable as first-time CLV ($10,500 vs. $21,219). This increased profitability can be attributed to a won-back customers' familiarity with the hotel, as well increased service by the hotel, since they better understand the customer's needs and preferences (Griffin & Lowenstein, 2001).

Once SLV is calculated and the lost customers have been ranked, the firm must generate appropriate win-back offers. Since firms have data on former customers purchasing habits and preferences, they have a unique opportunity to generate emotional value in the win-back process. In order to create a more open-minded mentality in the win-back process, firms need to be perceived as solving customer's needs and building relationships. Customers have more positive attitudes when they think firms are involved in customer-centric behaviors than when they think they are being sold to (Barlow & Maul, 2000),

To illustrate a win-back email, Figure 4 is a sample win-back email generated by the hotel. Through their win-back analysis, this former customer has been identified as having a high SLV, even among *millennial business travelers.* After analyzing the customer's previous history, the hotel discovered that he always booked rooms with a view, and complained about slow room service on 8 separate occasions. It's critical that the win-back offer display an understanding of why a customer left, acknowledgment of any previous misstep by the firm, and an understanding of the customer's current needs. As you can see below, the win-back email acknowledges that the customer has not booked a room recently, highlights a possible reason for dissatisfaction (poor room service), and offers a complimentary dinner.

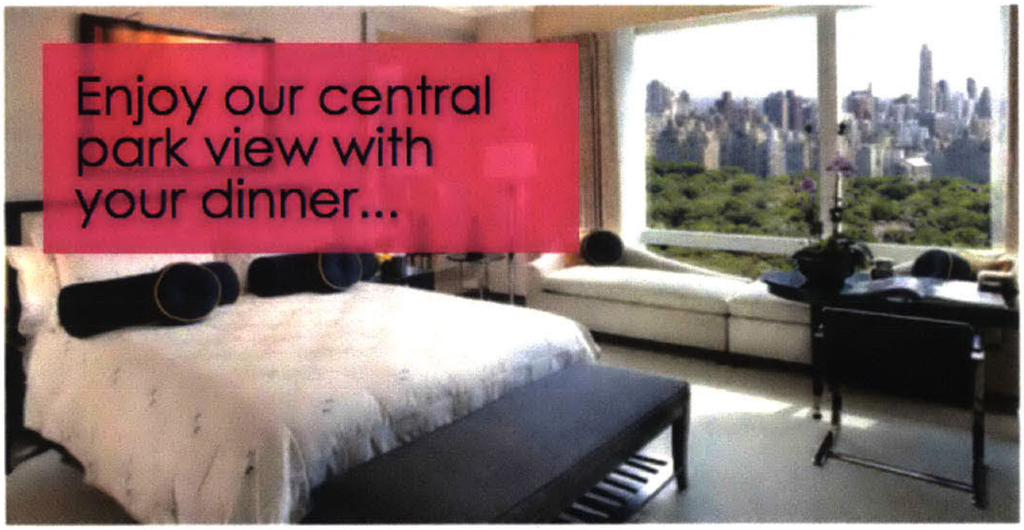
As with acquisition and retargeting, email marketing offers critical data that the hotel can use to test their win-back offers. The rate of unique emails opens, clicks, opens and quick closes, and abuse complaints, are essential for testing and iterating (Kaushik, 2011).

Figure 4: Win-back email

We miss you!

High-End Hotel < high-end hotel@hotel.com > 11:32 AM (2 hours ago)
to me

It's been a while since we've seen your face, and we miss you! Since the last time you stayed with us, we've made some serious improvements to our room service speed and quality. But don't take our word for it! Next time you book a room, please accept a free dinner on us.



5. Conclusion

Months ago, we embarked on a journey to understand whether value extraction opportunities were present in the three unresponsive customer types. This is a hard problem that is far from reconciled. As discussed earlier, scientist and researchers analyzing online emotions using Natural Language Processing among other techniques assumed silence equated to indifference. That assumption also holds true for practitioners. A digital marketing manager at one of the top 5 US e-commerce companies told us "an online customer that hasn't engaged with us in over 12 months is just taking up server space." But we think there is still hope, especially within the lost customer segment.

In the March issue of this year's *Harvard Business Review*, a marketing professor at Georgia State University cited several reasons companies should focus more energy on lost customers (Kumar & Bhagwat, 2015). These former customers have shown, from previous behavior that at one point they desired the firm's product and/or service. This familiarity makes reaching out to them a far stronger proposition than attempting to engage with a new prospect that has never heard of the firm. Thinking about this more conceptually, if we happen to bump into a friend that we haven't seen in years, we are far more likely to rekindle our friendship than if we had bumped into a complete stranger. This is similar to why technology like retargeting is so effective in converting consumers who have had some former touch point with the firm. Finally, as outlined earlier, advancements in enterprise customer relationship management tools have given firms unprecedented access to an ocean of transactional data. This data enables firms to better understand the first lifetime of a lost customer, which in turn helps create more effective win-back offers (Kumar & Bhagwat, 2015).

The concepts of 'Emotional Value' and 'Subjective Value' have demonstrated that being able to generate likability is a cost effective competitive advantage for any firm. In the aforementioned *Harvard Business Review* win-back study, lost customers who felt like they were listened to, and given a win-back offer that was relevant to them, were more profitable in their second-lifetime. This study is further evidence that emotional value can generate real impact on the P&L. Herb Kelleher, the co-founder, Chairman Emeritus, and former CEO of Southwest Airlines said "the intangibles are far more important than the tangibles in the competitive world because, obviously, you can replicate the tangibles" (Barlow & Maul, 2000).

But there are still challenges to overcome before firms are able to understand and engage with unresponsive customers. Most prominently is the issue of accurately understanding why a customer defected. Every piece of literature we explored seemingly assumed that understanding defection accurately was as simple as giving lost customers a phone call and asking them what went wrong. Another popular method for interpreting defection is the practice of sending customers an exit survey on their way out. This defection assumption felt like a red flag to us. To put this in a different context, when someone is in the act of ending romantic relationship, what are the odds they tell that person exactly why they are leaving? There is a reason why the phrase "it's not you, it's me" has found its place in our lexicon. Another example of the inaccuracy of exit surveys is illustrated in political exit polls. An exit poll is a survey of voters interviewed immediately after they cast their ballots, and serves to predict election results. However, in recent years some prominent mistaken predictions have occurred. For instance, in the 2004 US presidential election John Kerry was wrongly projected to win the electoral college, as well as the popular vote. In fact, George W. Bush's vote was underestimated in 41 of the 50 exit polls and John Kerry was incorrectly identified as the winner in five states (Pavia, 2010).

Besides defection, an effective win-back strategy relies on a firm's ability to understand the current needs and context of a lost customer. This is clearly a challenge since the lost customer is by definition, unresponsive. Adding to this complexity, the longer a lost customer has defected, the colder the trail gets, making the probability of win-back even more challenging (Kumar & Bhagwat, 2015).

Beyond defection and context, accurately predicting second-lifetime value is extremely important in win-back. In our hotel example, management needed to grade and segment lost customers by their predicted second-lifetime value. CLV and SLV calculations are inherently flawed because they rely on past behavior to predict the future. Again, with former customers, the more time lapsed since defection decreases the probability of accurately calculating second-lifetime value. So can the technological advances described earlier in our paper solve for these issues?

Techniques such as Natural Language Processing (NLP) and Statistical Learning powered by Machine Learning, along with Big Data Analytics may be able to accurately infer defection, context, and create impact on lifetime value of customers; although they still have limitations (Ferguson, 2012).

As (Manning & Schütze, 2000) remark: "A practical NLP system must be good at making disambiguation decision of word sense, word category, syntactic structure, and semantic scope." From a simpler but not simplistic perspective, machines still have a hard time reading between the lines, and the context on how humans create sentences and use words in multiple meanings and intentions are quite difficult to dissect and therefore, to understand.

Scientists like Rosalind Picard, co-founder of the company Affectiva – which claims to have built the largest emotional data repository with nearly 4 million faces – is researching how machines intelligence should include the skill of emotional intelligence, based on findings about how emotions interact with human intelligence (Khatchadourian, 2015). Picard is positioning herself at the cornerstone of the one of the next frontiers of Artificial Intelligence, influencing advancements in Machine Learning, Statistical Learning and Natural Language Processing altogether (McDuff et al., 2013).

Therefore, we can conclude: Yes, technological methods and techniques are available and potentially capable of augmenting the engagement of unresponsive customers. However, the current challenge is finding effective ways for humans to work with technology in order to produce desired managerial results. And this human-machine interplay has implications beyond just an implementation roadmap or an effective project management officer. The future seems to be marked by an imminent integration of neurocognitive sciences. These integrations will exponentially advance our understanding of unresponsive consumers' behavior, enabling a highly accurate study of their present and future actions and emotions.

6. Appendices

Appendix 1: New customer analysis

Tier		New Customers	Total 2015 Revenue	Average 2015 Revenue	Total 2015 Bookings	Average 2015 Bookings
	1	800	$11,200,000	$14,000	28,000	35
	2	1,500	$6,750,000	$4,500	22,500	15
	3	3,500	$10,500,000	$3,000	35,000	10
	4	1,500	$2,250,000	$1,500	7,500	5
	5	1,000	$300,000	$300	1,000	1
Total		8,300	$31,000,000	$4,660	94,000	

Appendix 2: Customer revenue analysis

Tier		Customers	Total 2015 Revenue	% of Total Revenue	Average 2015 Revenue	Total 2015 Bookings	Average 2015 Frequency of Bookings
	1	3000	$49,500,000	42.43%	$16,500.00	165000	55
	2	5000	$34,500,000	29.57%	$6,900.00	115000	23
	3	6000	$21,600,000	18.51%	$3,600.00	72000	12
	4	4500	$9,450,000	8.10%	$2,100.00	31500	7
	5	5500	$1,620,000	1.39%	$294.55	5400	1
		24,000	$116,670,000	100%	$5,820.00	383,500	

Appendix 3: Recency of purchase

Tier	Customer	Months since last purchase
1	4,000	0.00
2	5,500	1.80
3	5,500	3.50
4	9,400	10.40
5	7,600	13.90
	32,000	

Appendix 4: Customer lifetime value analysis

Revenue	**Year 1**	**Year 2**	**Year 3**	**Year 4**
Bookings per year	35	40	45	50
x Average booking order	$325	$400	$400	$400
Total Revenue	**$11,375**	**$16,000**	**$18,000**	**$20,000**
Costs				
Direct Cost	$7,963	$10,400	$11,700	$14,000
	0.7	0.65	0.65	0.7
Acquisition Cost	$3,413	$0	$0	$0
	0.3			
Retention Costs		$1,600	$1,800	$2,000
		0.1	0.1	0.1
Total Cost	$11,375	$12,000	$13,500	$16,000
Profit				
Gross Profit	$0	$4,000	$4,500	$4,000
Cumulative LTV	$0	$2,000	$6,500	**$10,500**

Appendix 5: Defection analysis

Tier	Defected Customers	Total Revenue in 2014	Average number of bookings
1	400	$6,000,000	50
2	120	$1,512,000	42
3	500	$6,000,000	40
4	300	$3,420,000	38
5	1,000	$10,500,000	35
	1,320	$27,432,000	

Appendix 6: Second-lifetime value analysis

Revenue	Win-Back Year 1	Win-Back Year 2	Win-Back Year 3	Win-Back Year 4
Bookings per year	15	20	35	50
x Average booking order	$325	$400	$400	$400
Baseline Revenue	$4,875	$8,000	$14,000	$20,000
Cross - Sell opportunities	$731	$1,200	$2,100	$3,000
	0.15	0.15	0.15	0.15
Information Value	$488	$800	$1,400	$2,000
	0.1	0.1	0.1	0.1
Total Revenue	$6,094	$10,000	$17,500	$25,000
Costs				
Direct Cost	$3,413	$5,200	$9,100	$14,000
	0.7	0.65	0.65	0.7
Win-Back Cost	$1,463	$0	$0	$0
	0.3			
Retention Costs		$800	$1,400	$2,000
		0.1	0.1	0.1
Total Cost	$4,875	$6,000	$10,500	$16,000
Profit				
Gross Profit	$1,219	$4,000	$7,000	$9,000
Cumulative SLTV	$1,219	$5,219	$12,219	**$21,219**

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