Expanding the Success of Behavioral Targeting with Service Resource Availability

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ABSTRACT:

Online behavioral targeting today is focused primarily on using electronic tags or "cookies" attached to web based consumer searches. From these tags algorithms, are developed to estimate customer potential. They are then are used to deliver targeted advertising messages. The current system is generally based on a limited linear predictive model to generate results. This paper provides a methodology that extends and expands that tagging methodology to other, non-direct contact product categories. We demonstrate how adding commonly available consumer service resources can be used to effectively increase the predictability of customer potential. In addition to avoiding privacy issues found in the current system, this methodology demonstrates the value of additional customer services resources as a method of improving general marketing capabilities for the firm.

Key Words: behavioral targeting, electronic tags and cookies, services resources as behavioral predictors, online research

I. Introduction

The concept of behavioral targeting, that is, offering customers news, information or another product or service based on some identifiable behavior demonstrated by that customer has likely always been part of marketing and promotion, at least as long there have been exchange marketplaces. For example, men's clothing store sales people commonly suggest a shirt and tie when a customer purchases a dress suit. Or, sales people offer accompanying pieces of china or pottery when a customer buys dinner place settings of a particular pattern. Even larger items can be driven by behavioral targeting, for example, golf club memberships are often offered to couples who purchase a condominium in a resort area. In these instances, these are natural "go-withs", that is, the marketer suggests that the purchase of one product can be enhanced, expanded or extended by offering something additionally. Behavioral targeting in these instances, is generally another good or service directly connected to the purchased or sought product and occurs "on-the-spot", e.g., at the point-of-purchase. It is commonly initiated directly by the marketing firm or sales person's observation and interaction with the relevant customer.

As the marketplace has diffused over the last decade, and as marketers have increasingly adopted technological innovations such as databases to help understand their customers and prospects, behavioral targeting has changed as well. Today, it is common for marketers to attempt to sell add-ons or to up-sell or cross-sell various products and services when a customer purchases a particular product or responds to some type of promotional offer (Payne, 2005). This idea of additional product sale being driven by captured customer behavioral data is the very heart of the concept of CRM (customer relationship management) (Blattberg et al., 2001). In many instances, in these types of CRM marketing, the firm is often willing to accept a relatively low margin on the product sold simply to develop the opportunity to sell or promote more profitable products or services later on.

The development of online marketing systems has created the next level of behavioral targeting. One of the most widely used is the system developed by Amazon.com to add-on, cross-sell and up-sell books and other products to customers based on their previous purchase behaviors with the firm. For example, when a customer makes an online book purchase from Amazon, the behavioral targeting system instantaneously scans previous book purchases made by that customer and others like him or her from the purchase database. The system then makes recommendations of other books or products which relate specifically to the customer's stored profile (www.amazon.com).

In the last few years, behavioral targeting has generated a whole new level of interest by marketers. This has come primarily through the development of various new analytical approaches which scan and evaluate the online behavior of customers and prospects. Today, behavioral targeting has come to mean how the marketer uses the information collected on an individual's web-browsing behavior, such as the pages they have visited or the searches they have made, to select specific advertisements to display to that individual (www.wikipedia.org/wiki/Behavioral_targeting). Marketers believe this type of analysis and technologically-driven message distribution helps them deliver their online advertisements to the users who are most likely to be interested in the marketer's array of offerings. Indeed, today a whole new genre of agencies and support organizations that focus on these types of analytics and delivery systems has developed.

The development of online behavioral targeting has come about primarily through the use of "cookies" or electronic tags which have been attached to the online applications consumers use on their computers. Using the data such as which search engine was used, what product or service sites were visited, how often those sites were visited and so on, marketing services firms such as Predicta BT (www.predicta.com), AdLINK 360 (www.adlinktech.com), Adaptlogic (www.adaptlogic.com) and others have developed. These organizations claim they can deliver electronically specific advertisements to particular customers who have signaled their interest by their previous behaviors. Marketers see these new systems as a way of reducing communication cost by selectively distributing messages only to those who have signaled some interest.

Simply put, the emerging opportunities in behavioral targeting today are based primarily on what the consumer does online. From the customer's actions, the behavioral targeting system identifies the product category or even the brand which might logically be considered as "being relevant" to that consumer. For example, if a consumer visits several automobile web sites and revisits the Ford site a second or third time, the belief is that constitutes a demonstration of consumer interest or intentions toward Ford brand automobiles. Therefore the ad targeting firm or system delivers up relevant Ford advertising based on those consumer behaviors at appropriate times in other online situations.

These new ad-serving systems have become quite popular over the last two to three years as consumers have developed more and more affinity for on-line shopping and purchasing. In spite of the huge growth in behavioral targeting usage, however, the systems in place, while technologically sophisticated, are still quite simple in their application, that is, they are primarily linear extrapolations of identifiable behaviors by individual consumers. Thus, for behavioral targeting to "work" the consumer must demonstrate some type of overt behavior which the marketer can capture, i.e., visit a web site or click through on a banner or purchase a product. That is required so that identified behavior can then be stored and combined with other consumer information to generate the next step in message delivery. Thus, most behavioral targeting approaches are quite limited in the information and knowledge on which they are based and quite restricted in terms of their ability to successfully connect consumers to potential future purchases.

Part of the difficulty in current levels of behavioral targeting is that the algorithms driving the message delivery are often based on limited consumer information or knowledge. Thus, the ability of the systems to suggest what advertising should be delivered or what add-on, up-sell or cross-sell products to offer is limited by the information that has been captured about specific incidences with customers and prospects. For example, Amazon knows what the consumer has purchased from them but, the system has little knowledge of what other, Amazon-inventoried products consumers may have purchased from Borders or Barnes and Noble or other online sellers or even from other bricks and mortar retailers.

Further, most behavioral targeting today is based on specific products or services which the customer accesses. If no product or service trail is evident, the algorithms used in behavioral targeting are often not applicable. In this paper, we demonstrate how an expanded and enhanced behavioral targeting system can be developed by moving from online product or service search, to more widely known services which might be available to the relevant consumer. In other words, we argue that services to which the consumer has access can enhance and improve and in some cases, offer totally new behavioral targeting opportunities for the marketing organization.

An additional value of the approach we propose is that it is not based on surreptitiously attached "cookies" or electronic tags but is based on observable activities by consumers, particularly with various services they employ for other purposes. This helps avoid some of the present hue and cry by the privacy advocates.

II. Expanding and Extending Behavioral Targeting

This study expands and extends the marketer's capabilities in using behavioral targeting by adding in other, primarily service-based resources to the information mix used to generate the delivery of additional communication or messages. These additional bits of information allow the marketer to improve the results of the current behavioral targeting algorithms through a triangulation system which is more powerful than the present linear algorithms presently in place. As before, in our approach, we use widely available bits of knowledge about consumers that are not considered private and which may be used with the knowledge and permission of the consumer. All of the data used in this expanded behavioral targeting approach has been volunteered by the consumers involved. Each responded to an on-going, panel-based research study which has been conducted in the United States since 2001 and in China since 2006.

The premise for this behavioral targeting expansion is quite simple. As before, behavioral targeting is commonly limited to the observed web-based behaviors of consumers in specific product or service categories. Thus, consumer behavioral knowledge can often be limited to relatively short-term consumer activities. Or, if the information is used over a longer period of time, the knowledge gathered from the "cookies" or other product-specific tags marketers or third parties have been able to implant from on consumer-initiated web activities, may become irrelevant in a very dynamic marketplace.

In our experience, most behavioral targeting systems have a rather limited "shelf life", that is, they are limited to the most recent search or online exploration and thus, often have little or limited "history" on which marketers can make advertisement serving decisions.

Block and Schultz, 2009 and Schultz and Block, 2010 have demonstrated that in many retail situations, where a preponderance of current behavioral targeting activity is concentrated, consumers do not enter the purchase arena as "blank slates", e.g., with no previous background or knowledge about the products they are seeing, the stores they are visiting, the brands they have tried and the like. They bring a wide variety of past history and experience into what has been termed the "Retail Theater" (Schultz and Block, 2010). It is therefore a combination of factors that influence how individual consumers shop the retail store, what products they buy and what they ignore. They have demonstrated, for example, that the previous media exposure by consumers prior to the store visit, to both retail and manufacturer's promotional activities, has a major impact on what is actually purchased in the retail store. Thus, marketers cannot base promotional decisions simply on out-of-store or prior-to-the-store visit variables or even variables which exist only in the store. Instead, they must understand the wide variety of experiences and exposures which consumers have to make relevant behavioral targeting decisions.

Based on these concepts, we argue the same situation is true in online shopping situations. Consumers have reservoirs of knowledge and information they bring to the way they use online activities. The challenge, of course, is that most marketers have no knowledge or background on what those previous consumer marketing exposures have been unless they occurred within the specific marketer's or advertising delivery system and have, therefore, been captured in some type of database which can be analyzed separately.

Today, there are resources now available to marketers, particularly in the United States and China, which can explain, enhance and in some cases even predict a consumer's interests. These can be combined with existing online behavioral data and targeting approaches to make them even more effective.

III. Adding Consumer Services to the Behavioral Targeting Mix

The data used in this paper to expand and enhance behavioral targeting is based on the syndicated media and marketing consumption studies which have been conducted in the United States since 2001 under the trade name SIMM (Simultaneous Media Usage Studies) and in China since 2006 under the trade name China Quarterly Media Studies. Both studies are conducted by BIGresearch, Columbus, OH, (www.bigresearch.com). In this analysis, we use only the SIMM data from the U.S. to illustrate the potential now available to marketers.

SIMM studies are conducted twice yearly through an online methodology in which a representative sample of the U.S. population completes a questionnaire describing their media usage and consumption in 31 online and offline categories. In addition to reporting their media usage, consumers also report on their favorite retailers, major product purchases planned, services they either have acquired or to which they subscribe along with traditional demographic and psychographic variables. Typically, the SIMM study generates approximately 20,000 responses in each wave. Since the studies have now been conducted for nearly a decade, approximately one-quarter million responses are stored in the database. The length of time over which the studies have been conducted and the size of the sample base have made the analyses conducted on the data quite reliable.

The data used in the study reported below comes from SIMM 14 which was gathered in June, 2009 so the data is quite current. It consists of 22,641 responses which proportionately represent the 14 age-sex cells used in the U.S. Census.

The basic premise of this study is that various, identifiable services which consumers use and to which the marketer has access can be used to enhance and expand existing behavioral targeting systems. Of most importance is the ability of the enhanced behavioral targeting system to move beyond directly related consumer behaviors such as book purchases or online searches for products and services to build a holistic view of the specific consumer. Thus, the system we demonstrate below uses what would seem to be unrelated consumer behaviors to predict purchases in different product and categories.

A. Service Variables in the Model

To test our concept, we have used three widely divergent services to which SIMM survey respondents say they either use or have access to. Those are: (a) social media such as Facebook, Linkedin, MySpace and Twitter, (b) ownership of video game consoles which can be used for online or offline game playing and (c) credit card ownership. These variables were randomly selected simply to put the concept of enhancing behavioral targeting to the most stringent test possible.

We posit two primary results from the addition of the identified service components which can enhance simple reported use of product categories or tracking of online consumer search behaviors.

One: The addition of availability of services the consumer has access to will significantly expand the predictability of product use in the category when compared to simply knowing the reported or observable behaviors of consumers.

Two: The addition of the service availability of various facilities, will vary significantly in terms of predictability across the categories tested. This idea of differences in predictability based on product category is an important one in behavioral targeting since most current systems use one basic algorithm to predict across a wide variety of product categories.

We now describe the methodology which was used to develop our analyses.

B. Reported Online Behaviors

The analysis below is based on the reported online behaviors of the 22,641 consumers who participated in the SIMM 14 Study, conducted in June, 2009. Those behaviors are illustrated in Exhibit 1.

Exhibit 1

Like To Do Online for Fun & Entertainment

	Percent		Percent
Shopping	38.2	Music News	13.8
Weather	38.0	Locate Old Friends	13.4
Movie Reviews/Schedules	27.6	Visit Video Sharing Sites	13.2
View Photos from Friends	26.3	Stock Market News	13.0
Sports News & Scores	22.9	Share Stories with Friends	11.2
Research/Ideas for Hobbies	21.8	Adult Entertainment	10.6
Video Games	18.7	Horoscopes/Astrology	9.4
Watch TV Shows	18.1	Genealogy Research	5.9
Online Auctions	16.9	Fantasy Sports	5.9
IM/Chat	15.7	Gambling	5.1
Celebrity Gossip	15.1	Get Advice from Friends	4.7
TV Reviews/Schedules	14.7	Online Dating	3.3

As shown above, the top six reported uses of online activities by respondent were (a) shopping, (b) get weather information, (c) gather movie information, (d) gather sports news and scores, (e) research or search for hobbies. All of these categories generated more than a 20% sample response rate.

Clearly, knowing the specific reasons for the online activity is important, yet, the wide and varied use of online systems does little to help the marketer know much about the various consumers and prospects. For that, aggregation of the customer data is needed. The next step was to conduct a factor analysis on why consumers go to online systems and what they do when there.

Exhibit 2

Factor Analysis of Reported Online Usage

(Explains 39.7% of Variance)

	Features	Friends	Sports	Video	Fantasy	Search
Celebrity Gossip	0.65					
Movie Reviews/Schedules	0.57					
TV Reviews/Schedules	0.56					
Music News	0.54					
Share Stories with Friends		0.72				
View Photos from Friends		0.60				
Get Advice from Friends		0.60				
Locate Old Friends/Classmates		0.49				
Sports News & Scores			0.76			
Fantasy Sports			0.58			
Stock Market/Business News			0.57			
Video Games				0.61		
Visit Video Sharing Sites				0.56		
Watch TV Shows				0.52		
Online Dating					0.55	
Adult Entertainment					0.51	
Gambling					0.46	
Horoscopes/Astrology					0.45	
Online Auctions					0.61	
Research/Get Ideas for Hobbies						0.56
Shopping						0.53
Weather						0.40

A factor analysis was performed on the 24 online activity variables in Exhibit 1 to simplify the analysis. Using a varimax rotation the resulting factors are shown in Exhibit 2. Loadings of less than .40 are deleted to make the exhibit easier to read. Factor scores were computed for the next step in the analysis. As shown above, the factor analysis explained nearly 40% of the variance, a fairly strong indication of the power of the model.

This analysis generated six factors. They were labeled as (a) features, which consist mainly of entertainment news, (b) friends which are personal relationships, (c) sports news and scores, (d) video which are web-driven games and activities, (d) fantasy which has to do with various types of personal services and (e) search which consist primarily of information gathering.

C. Product or Purchase Usage

One of the key elements of the SIMM database is that it collects data not just on media usage but on shopping habits and purchase behaviors as well. In our analysis, we identified the heavy users of five radically different product categories. Those are shown in Exhibit 3

Exhibit 3

Reported Heavy Users by Product Category

	Percent
Sporting Goods	11.3
Interested in team sports	
Home Appliances	12.5
Plan in next 6 months	
TV	11.8
Plan in next 6 months	
Women's Clothing	12.9
Purchase every two weeks or less	
HBA	14.5
Purchase every two weeks or less	

The selection of these five product categories was made deliberately to put as much stress on our concept as possible, i.e., that service availability or usage could be used to predict consumer behaviors, a key element in any behavioral targeting approach. As shown, the five categories selected were (a) sporting goods where SIMM respondents signify their interest in team sports, (b) home appliances, e.g., large considered purchase products such as refrigerators, washing machines, dryers and the like. The qualification was that consumers indicated they planned to purchase one of these appliances in the next six months. The six month classification also identified consumers who planned to purchase a (c) television set in the next six months. (d) Women’s clothing is a radically different category. The screener for customer usage of this group was making purchases of clothing every two weeks or less. The final category was (e) heavy usage of HBA or health and beauty aids such as shampoo, bath soap, shaving accessories and the like. This was determined by the respondent's claim of shopping in this category every two weeks or less.

These elements, i.e., how and for what purpose the internet is used, and the five product categories selected were then combined into one model. That provided the base for the analysis which follows.

IV. Service Availability and Usage

To test our premises, we selected three radically different services which might are generally available to the sample customers previously identified. Those were (a) consumers regularly using various forms of social media, i.e., Facebook, Linkedin, MySpace and Twitter. The incidence of Social Media usage is shown in Exhibit 4.

Exhibit 4

Use of Social Media

	Percent Regularly Using
Facebook	23.2
LinkedIn	2.9
MySpace	8.7
Twitter	3.1
Social*	0.444

*Number of sites per household

As shown, FaceBook is the dominant social media form used by the SIMM sample with MySpace trailing and only limited numbers of respondents using Linkedin and Twitter. Of the sample, the average number of social media forms per household was approximately 4.5.

The second service form chosen was usage of Video Games. The premise here was that ownership of various video game consoles indicated a general acceptance of web-delivered services. Therefore, this was believed to be an indicator of online activity and participation. The incidence of video game consoles among the sample is shown in Exhibit 5.

Exhibit 5

Video Game Console Ownership

	Percent Owning
Nintendo Wii	23.0
Xbox 360	14.0
PlayStation 3	9.4
Gamebox*	0.464

*Number of boxes per household

As shown above, Nintendo Wii is the leading online gaming console among the SIMM sample with 23% of the sample claiming ownership. That was followed by Xbox 360 (14% ownership). PlayStation 3 trailed with 9.4% penetration. Of the total sample less than 50% of the sample (46.6% reported owning a video game console).

The third and final service form chosen was ownership of a credit card. Here, a fairly broad range was used from the leading bank-issued cards such as Visa and MasterCard to financial organization credit cards such as Discover and American Express to individual retail store credit cards. Visa was the leading bankcard and Discover the leading financial institution card. Date on ownership is shown in Exhibit 6 below.

Exhibit 6

Credit Card Ownership

	Percent
Visa	60.1
Master Card	46.8
Store Credit Card	23.5
Discover Card	21.0
American Express	15.6
Cards*	1.670

*Number of cards per household (ignores multiples of same type

The total number of cards per household in the sample was 1.67. We ignored multiple cards of the same type in each household. As shown, Visa and Master Card dominate the ownership among the SIMM panel.

V. Understanding the Impact of Service Facilities on Heavy Users

The first step in the analysis was to combine the nine variables, six product categories and three service variables into a set of regression equations. The goal was to determine which of the nine variables best predicted heavy users in the product categories. These regression outputs are shown as a series of charts which have been derived from the regression models. Each is discussed briefly simply to illustrate the process. The real value is found in the second equation which illustrates whether or not the addition of the service element availability predicts improvements in the model. The following regression equations are demonstrated by the appropriate standardized regression coefficients. Because the sample size is so large (n=22,641) virtually all of the coefficients, and all of the equations are statistically significant.

Exhibit 7 illustrates the output of the regression model on Interest in Team Sports. As might be expected, usage and involvement in online sports activities is the major predictor. The second most important factor is ownership of a Gamebox. Interestingly, use of online Search and availability of Credit Cards have little to do with the Interest in Team Sports.

Exhibit 7

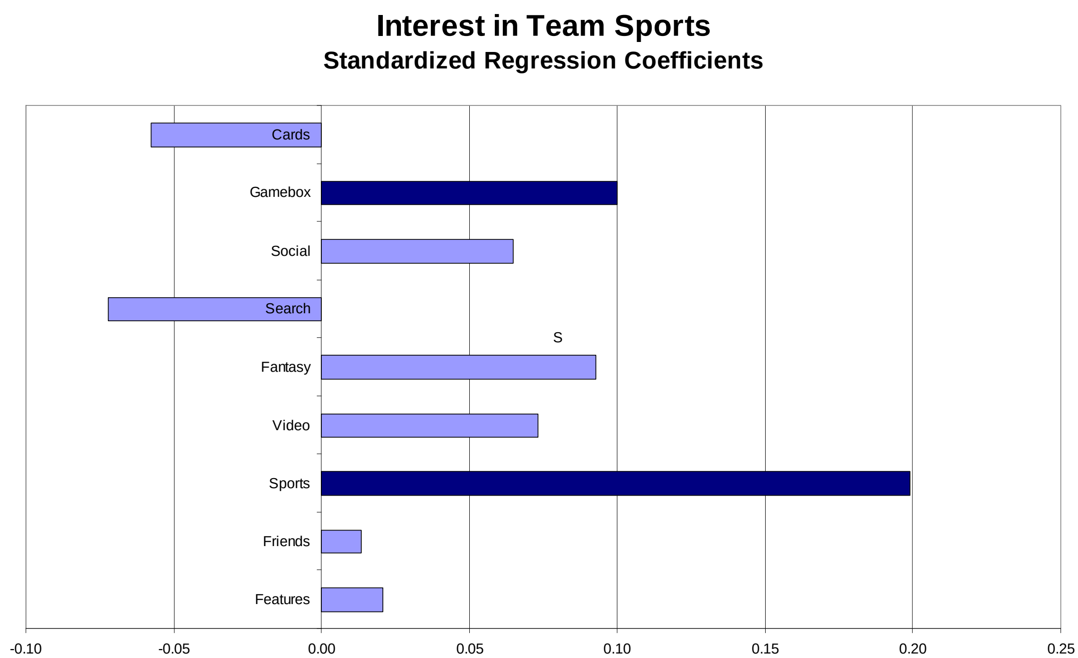
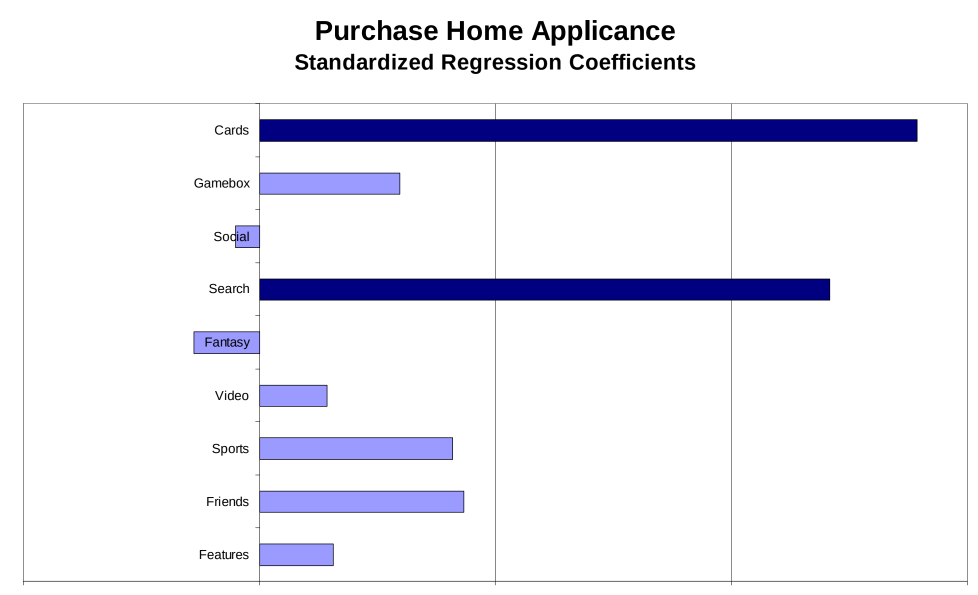


Exhibit 8 presents the results of the Purchase Home Appliance analysis. As shown, the availability of Credit Cards and the use of online Search are the two major factors which predict the identification of people who plan to purchase a major Home Appliance in the next six months.

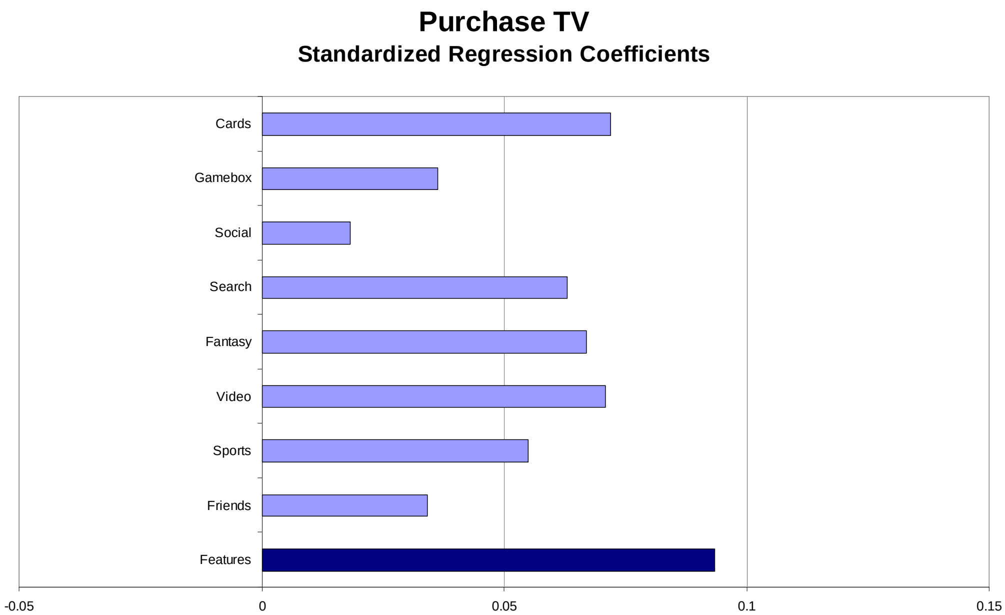
Exhibit 8



Interestingly, the use of Social Media and Fantasy activities on the web has a negative impact on predicting Home Appliance purchase interest.

Exhibit 9 illustrates the variables which best predict individuals in the SIMM panel who plan to purchase a Television set in the next six months. As shown, the use of the Features factor from the previous analysis is the primary predictor with availability of Credit Cards and ownership of a Video Game console a fairly close second.

Exhibit 9



Of note is that none of the factors in the Planned Purchase of a Television equation has a negative impact on plans to purchase a new television set.

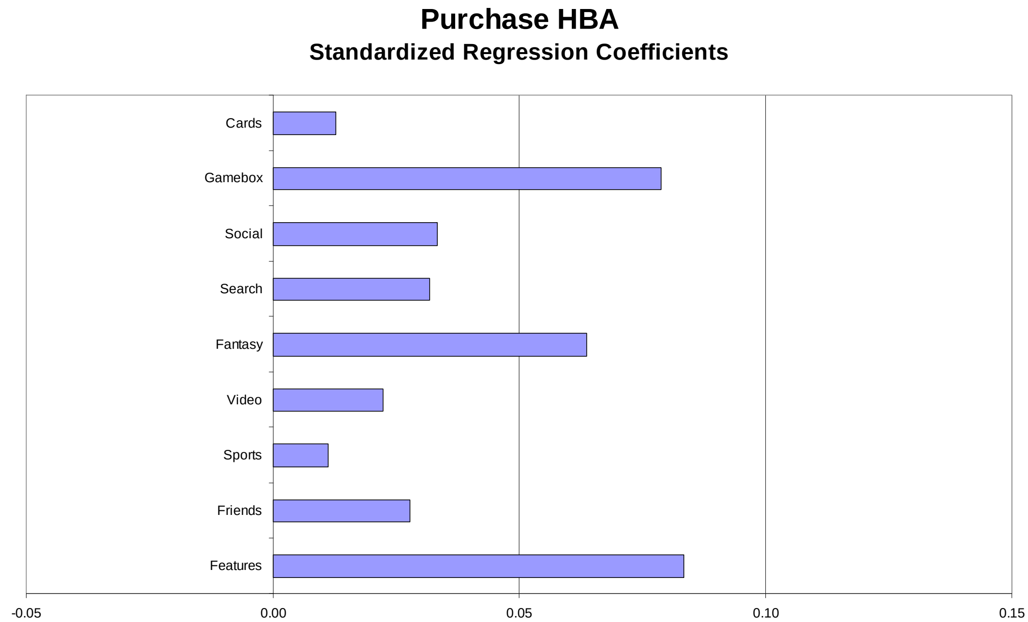
Exhibit 10 shows the impact of the variables on predicting heavy user purchasers of Women's Clothing. Recall, a heavy user is defined as a person who says they shopped for Women's Clothing every two weeks or less.

Exhibit 10

The use of the Features factor in online activities was the best predictor of heavy women's clothing purchasers. Recall that factor was made up of Celebrity Gossip, Movie Reviews/Schedules, TV Reviews/Schedules and Music News. This analysis certainly supports the marketing assumption that those women who are most interested in entertainment, music, movies and the like are also the ones who do the most shopping for women's clothing. What is not so obvious is that the availability of a Credit Card, the ownership of a Gamebox and the use of Social Media all of which are also strong predictors of being a heavy user in the purchase of Women's Clothing.

Exhibit 11 illustrates the factors which best predict the heavy purchasers of HBA (Health and Beauty Aids), that is, they report they shop for HBA products every two weeks or less. As shown below, all factors have a positive contribution to explaining heavy purchasers in this category. The factors that predict heavy usage are not so obvious, however. For example, as shown below, the Features factor on online usage (similar to the heavy user in Women's Clothing) is the primary predictor closely followed by the ownership of a Gamebox. None of the variables tested had a negative effect on predicting the identification of the heavy user in the Purchase HBA category.

Exhibit 11



What is most interesting about the analysis above is that each product category is radically different from the others investigated. Thus, it would appear that if the service variable were added to behavioral targeting algorithms, a separate analysis would be required for each category. That would seem to challenge the assumption that single variables can be used to build behavioral targeting delivery systems except in the directly related categories, i.e., books or directly marketed and identifiable products. Thus, our suggestion that today's online behavioral targeting segmentation approaches are quite simplistic and of limited value to the marketer likely holds true.

The other noticeable thing about the regression equations developed from the SIMM data is that no single element, with the obvious exception of Team Sports is really a defining predictor of heavy usage in the product category. Thus, it would seem that expanding the basic premise of behavioral targeting is in order and should be considered by marketers going forward.

V. Does the Addition of Service Availability Improve Behavioral Targeting?

Based on this initial analysis, it does appear that the addition of various services available to consumers might significantly improve the present limited category, linear behavioral targeting methodologies being used. The results of the analysis described above provide the following levels of improvement in identifying the potential customers for behavioral targeting.

Exhibit 12

Service Improvement of Product Identifiers

	R^2 with Services	R^2 w/o Services	Percent Improvement
Home	0.048	0.028	69.0
Women's	0.057	0.036	59.5
HBA	0.029	0.021	35.8
Sports	0.092	0.075	22.4
TV	0.041	0.034	20.0

As shown, when the three services are included in the models, e.g., use of social media, ownership of game consoles and availability of credit cards, the percent improvement in identification ranges from a high of 69% for Home Appliance planned purchases to a low of 20% for planned Television Set purchases within the next six months. Clearly, this level of increased identification to existing behavioral segmentation approaches is quite significant and would be important to marketers.

The value of this new type of behavioral targeting is that the three services which we included in our analysis, while dramatically different in terms of their perceived relationship to the purchase categories, are relatively easy for marketers to capture and use. They obviously reduce the perceived questions on privacy invasion which the use of “cookies” and other electronic tags create in the minds of the consumers and regulators.

While we used a proprietary database for this analysis, the variables such as credit card ownership, use of social media and ownership of videogame consoles, are quite easily obtained by marketers wishing to develop this next stage of behavioral targeting. So, it would appear that the addition of services availability to consumers provides a very useful variable to improve behavioral targeting, particularly when the targeting is focused on online usage.

VI. Opportunities, Limitations and Next Steps

The opportunities developed and demonstrated in this extended and expanded approach to behavioral targeting, through the use of identifiable consumer service variables, provides what we believe are major opportunities for all marketing organizations. As more and more consumer purchases are driven by and occur in the online space, marketers must expand and extend the relatively primitive interaction approaches that have been developed to this point. While behavioral targeting, tied to known product purchases in established categories, have the potential to increase product and service sales as Amazon.com has so ably demonstrated, the real issue for marketers is what to do in categories which cannot or are not dependent on previous purchases or more importantly on the tracking of consumer search routines. Large numbers of products and services simply don't fit that add-on, up-sell or cross-sell model. The use of consumer service availabilities appears to provide a substantially new, effective and low cost method of improving and enhancing existing behavioral targeting approaches. The example developed for this paper is, we believe, only the tip of the iceberg and holds great promise for the future.

In terms of limitations, clearly the examples we have presented here have limitations. It is drawn only from a U.S. population base. Whether or not the modeling will hold true in other markets or in other data sets is not known. We believe the findings are transferable, but, that has yet to be proven.

There is also the limitation of the variables used in this model. Our goal was to demonstrate the potential for the model in a wide range of product categories. The SIMM data provides customer-stated purchase intent in several of the purchase categories used in the model. Whether or not those intentions were carried out is not known. It would be a simple task, however, to re-survey respondents to determine whether that intent actually played out in the marketplace. We have not done that.

Similarly, the three service variables were deliberately chosen since they have so few perceived similarities. While some of these are clearly evident, that is, people who follow sports online are ones who most likely would own game consoles, others, however, create quite a stretch in credibility. For example, the relationship between online search behaviors and the intent to buy home appliances in the next six months would not seem to be intuitively connected. Similarly, the ownership of a Gamebox and the practice of frequently shopping for women's clothing is a unique relationship that likely would never have surfaced in traditional online behavioral targeting. Are there better variables than the ones we chose? Possibly. That is clearly the future direction of our research.

In terms of next steps, we plan to continue to develop and extend these first initial results in improved behavioral targeting. That will likely include the use of other variables, other product categories and other services available to consumers. We believe that we have demonstrated an interesting new area for research and development for service area marketers. No longer should the focus be only on the marketing of services, we can now start to look at consumer usage and availability of services as key elements in developing the overall field of marketing. Services clearly can predict consumer product use and consumer product use might well be the future of developing better models of identifying which products and services consumers might be interested and in which they might accept new service approaches. In short, we believe this type of service and product integrated research provides a bright new opportunity for scholars around the world.

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