SELLING MEDIA IN A MULTI-PLATFORM WORLD

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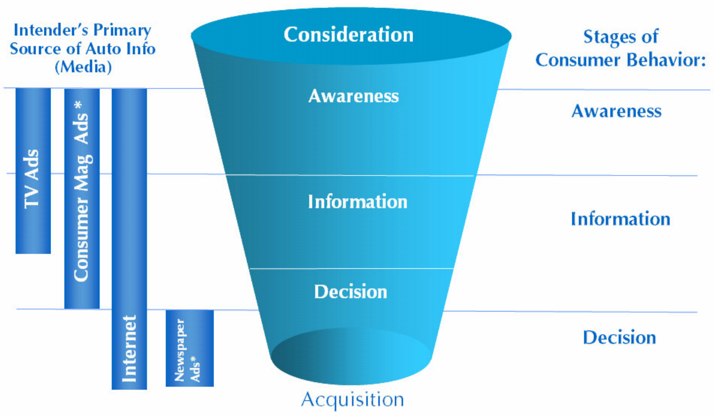
Introduction

The vast amount of available information sources has resulted in a more sophisticated set of consumers who actively seek facts and advice to help them in their purchase decisions. In the Automotive industry we know that complex decisions are required and consumers spend much time in the evaluation of available products before the purchase is made. According to Schoell and Guiltinan, "The more money involved relative to one's disposable income, the greater the perceived psychological risk and the more information the consumer will seek" (1992). In fact, most automotive sales and marketing professionals know that today's consumers come to the dealership more educated and better prepared than consumers of the past. As a result, most automotive professionals know that in order to maintain their market share they need to provide information to consumers throughout the various stages of the purchase process.

In recent years, automotive marketers have recognized the importance of communicating with consumers throughout the decision process. Starting at the upper funnel with 'intenders' and ending at the lower end with buyers, marketers are using different media sources across the purchase funnel to help educate and inform consumers. Figure 1 below highlights the differences in media usage patterns across the purchase funnel.[1#*]

Figure 1
COMMUNICATING WITH INTENDERS FROM ONE STAGE TO THE NEXT



There are many elements that go into the final purchase or lease of a new vehicle. The decision not only includes the marketing/advertising component but also elements that relate to factors from an industry perspective (dealers, manufacturer incentives, new product introductions/redesigns etc) as well as the all important quality and image of the brand.

As the illustration shows, research of the purchase funnel identifies three areas of behavior that takes place when the consumer is in the market for a new vehicle. The first stage is *awareness*. At that time, the intender is building their shopping list and assessing their vehicle needs. During the *information* stage, the consumer is assessing what vehicles will remain on the shopping list. At this point, the list begins to come down in size. The final stage is *decision*. Here the primary focus is price point, the shopping list is shorter and it is at this time that incidence of dealer visits begins to increase.

[1] : CNW Marketing/Research/Time Inc;
[#] Internet reflects manufacturer, dealer and 3rd party sites
[*] Includes print and online

In a true marketing fashion, the purchase funnel illustrates the importance of communicating with intenders from one stage to the next—beginning with the upper funnel. While we have information that quantifies the use of multiple media sources at various stages, up until now, we did not have research that can demonstrate the impact of combining media —specifically print and online—in reaching consumers who have recently acquired a new vehicle.

Automotive marketers have recognized the changes in consumer behavior and re-allocated their advertising spending. In the early 1990's automotive advertisers in the United States were spending about $3 billion per year in magazines, while spending on the early stage Internet was essentially non-existent. In 2007 it is forecasted that 40-45% of total automotive advertising will be spent on the combination of print and online media. As media consumption patterns continue to change due to increased time spent on the internet, marketers need a method to assess reach and frequency across media sources to ensure that their marketing dollars are being spent efficiently. But acquiring sufficient insights about cross media usage from a single respondent is challenging. Creating a sufficiently detailed survey comes at a cost: longer surveys have lower survey response rates, increased missing data rates, and overall higher study costs. Additionally, there are numerous findings indicating that even when consumers do complete a lengthy survey, intra-respondent variation decreases notably suggesting respondent "fatigue" /"burn out" that make the results less reliable.

While some off- and on-line publishers offer "packages" of different media which can carry coordinated messages, audience estimates are provided only within a specific medium. As such, both marketers and publishers have asked the research community for an approach to estimate audience reach and frequency accurately across combinations of media usage.

Therefore, the primary objective of this paper is to present an *integrated cross media assessment methodology*. We begin by presenting findings of three different data fusion techniques that enable researchers to integrate detailed insights from different, yet similar, consumers thereby addressing the survey challenges of obtaining all data within the same respondent. Here, we compare and contrast different methods which are an extension of work from other researchers (Song, 2001, Napier & Mattlin, 2005; Collins & Pingitore, 2007). Next, we present a case study from Time Inc. showing the unique opportunity to leverage fusion techniques to enhance planning efforts and increase the actionability of targeting media efforts. Specifically, we demonstrate that data fusion is an effective methodology that provides media planners and advertisers the ability to assess concentration, growth and market profiling in greater depth of detail than current reach statistics.

Background

J.D. Power and Associates conducts two media studies annually. The Power Car and Truck Media Reports, known as the Offline Media Reports (OMR), surveys new vehicle buyers about their preferences in traditional media such as, magazines, cable television channels, and radio formats. The Online Media Study (OMS) in contrast surveys new vehicle buyers about what information they seek on the internet and which web sites they visit.

As the two studies are designed and conducted separately, it is impossible to analyze them together without the help of statistical matching. To increase the value of our information and enable media planners and publishers to use the two studies jointly, a data fusion technique is applied to fuse the two studies together to create a combined tool: The Integrated Media Planning Tool (IMPT).

As most data fusers know, there are numerous statistical approaches that can be used to successfully fuse together different databases (Song, 2001). As such, we evaluated the effectiveness of three different statistical approaches to fuse together the OMR and OMS the datasets.

Sample Description

The Integrated Media Planning Tool was developed by fusing together two samples of new vehicle buyers:

1) The Offline Media Reports (OMR) surveys new car/truck buyers. The sample source for OMR was R.L. Polk's vehicle registration database of new vehicles registered from May 2005 through April 2006. The database was stratified by vehicle model and a random sample was selected within each stratum. Historical response rates for each model were used to determine the total number of mail outs by model to ensure each model met a minimum quote of 50 returns. This final sample was then weighted up to the total sales for the given time period. The total OMR sample size was 43,953 of which 38, 650 were internet users and 5,303 had no access to the internet. Because we needed to fuse traditional media usage to online media consumption behaviors (i.e., people with internet access), only OMR respondents with internet access (n= 38,650) were used within the fusion process. By starting with only the internet users within OMR, estimation errors of online media consumption were minimized. The 5,303 non-internet-using respondents were brought back into the final fused dataset so that total OMR average issue audience rates would be representative of the new vehicle buyer population. Data was collected via a 12-page mail questionnaire.

2) The Online Media Study (OMS) also surveys new vehicle buyers and utilizes R.L. Polk's vehicle registration database as of new vehicles registered between January, February and March 2007. The sample was taken and weighted similarly to the OMR. Respondents were mailed a postcard inviting them to participate in an online survey. The total online sample was 11,522 but only 10,755 were retained for fusion as 767 respondents did not provide responses to gender or age (which are critical variables).

Statistical Approaches Used for IMPT Data Fusion

Approach 1 we refer to as Unconstrained One-to-One. In this approach, the OMS database was identified as the recipient file and the OMR as the donor database since the OMS was smaller in size. Within this approach we first randomized the recipient file (OMS) to avoid order effect. We then calculated the distance to each recipient and fused the data from the donor with the shortest distance. When multiple donors were found, we randomly selected and applied the data from one donor. This process was repeated for each recipient until all records in the recipient data set had a donor. The resulting size of the fused dataset was equal to the size of the recipient file (N=10,755, see the results section below for details).

With this approach, a donor can be allowed to donate data multiple times. However, given the size of the donor data, we have found that the occurrence of multiple donations was relatively small and the difference between single vs. multiple donation was negligible.

Approach 2 we refer to as Constrained One-to-One since data transportation was symmetrical (i.e., we assumed no primacy of one file over another) and we retained currency values of the primary outcomes. Similar to the unconstrained approach, the datasets were first randomized to avoid order effect and the distance to each respondent was calculated Unlike the unconstrained approach, however, the size of the fused dataset was larger than each of the original files (fused dataset=m+n-1) as it contained fractions of records from both data sets.

Within Approaches 1 and 2, we also tested two different distance algorithms to determine which is more effective in matching respondents between each database. We compared a ***Euclidean*** measure to that of the ***Mahalanobis.*** The results of which will be presented below in the discussion of distance metrics.

For Approach 3 we leveraged the work of Jim Collins (2007) and developed a more dynamic method of using respondent classification as a way to select the critical matching variables. This approach we refer to as Dynamic Constrained fusion. As will be described below, the selection of matching variables were made based on an iterative empirical examination that determined the most important variables within a sub-set of respondents.

Matching Variables and the Process of Segmenting the Total Sample

As with any fusion effort, we began by identifying common variables within both datasets and divided them into critical variables, or those that must be matched and non-critical variables, or those that are desirable but not essential to match (Song, 2001). Even though the two studies were designed and conducted separately, there were several common variables including demographics (e.g., gender, age, income, respondent residential region), vehicle information such as vehicle model, origin (domestic vs. import), vehicle type (car vs. truck) and segment (compact, sport utility, etc.). Also available were individual difference factors such as attitudes toward driving and factors influencing the purchase/lease decision.

The specific variables identified as critical vs. non-critical varied across each approach and are displayed in Table 1 below.

Table 1

	Approach		
	1	2	3
Vehicle			
Type (car vs. truck)	C		
Super segment		C	
Segment			C
Make	Not used due to too many categories		
Model			
Origin			C
Region	N	C	C
Demographics			
Gender	C	C	C
Age	N	N	N
Education	N	N	N
Marital status	N	N	N
Number of adults	Not use (different distributions)		
Children	N	N	N
Ethnicity	N	N	N
Income	N	N	N

C=Critical variable; N=Non-critical variable

	Approach		
	1	2	3
Important factors in purchasing/leasing vehicle			
Fuel economy	N	X	X
Dependability …	Not used due to different distributions or skewed		
Quality of workmanshi			
Reputation			
Low price	N	X	X
High resale value	N	X	X
Psychographics			
A great deal of pride	Not used due to different distributions or skewed		
Friends and family thir			
Comfortable vehicle…			
Like to customize …			
Extended trip…			
Challenging road…			
Other			
Hours on internet	N	X	X

N=Non-critical variable; X=Not used (small effects)

Selection of which variables were critical vs. non-critical was made iteratively and based first upon selecting those factors that are well known to influence the media consumption. Additionally, various empirical criteria such as, sample size and shape of the respective distributions were evaluated. We made sure that sub-samples created by the critical variables all had sufficient samples within both the OMS and the OMR datasets. Variables were excluded if they were highly skewed or had different distributions between the OMS and the OMR datasets.

For Approaches 1 (Unconstrained) and 2 (Constrained), the critical variables included vehicle super segment (8 categories), gender (2), and region (4). Their combinations result in a total of 64 sub-samples.

For approach 3 (Dynamic Constrained), we again selected gender and respondent residential region as critical variables but increased the granularity by using vehicle segment (26 categories) rather than super segment as we believed this would better preserve the Average Issue Audience (AIA) for each of the magazines covered in the study. In addition, the vehicle origin was also added.

The full crossing of these variables within Approach 3 resulted in a very large matrix of 208 combinations. Even though our original datasets had large sample sizes, this matrix resulted in some cells having small or no data. As a result, we decided to determine empirically which of these four variables reliably predicted readership behavior. We created a measure of the number of magazines read as our dependent variable by summing the total magazines read in the past six months. Since the distribution of this variable is skewed to the right, it was transformed to an interval variable with nine scale points by combining some of the counts into categories so that it was closer to a bell shape.

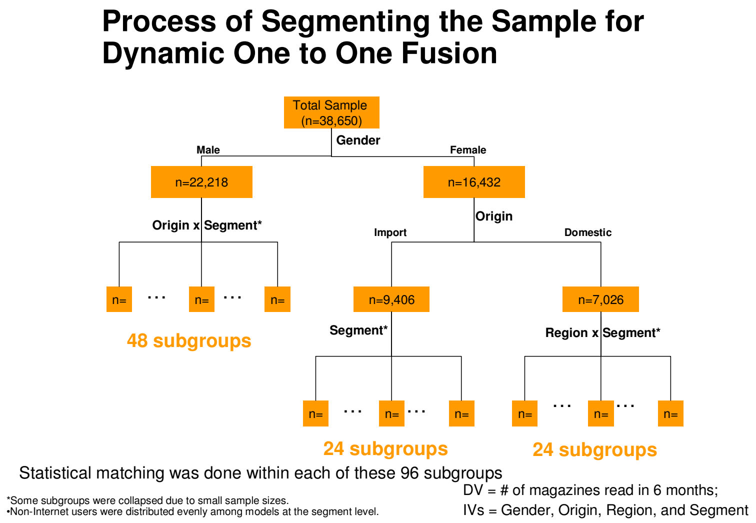
Using a standard four factor ANOVA[2] we recursively partition the data into increasingly homogeneous subsets by using the most significant main effect variable at each step. Essentially, our aim was to partition the total sample (i.e., tree) into sequentially smaller groups (i.e., branches).

We started by fitting all four main effects and interactions in a model to explain the dependent measure of magazine readership. Main effects and interaction were considered significant at $p < .10$. Results from this analysis showed that gender was the most robust main effect ($p < 0.0001$). Thus, in the next step the overall sample was split into male and female. At this step, a three-way ANOVA of vehicle origin (2 levels), vehicle segment (26 levels), and respondents residence (4 levels) and their interactions was fitted separately to the male and female samples. This splitting and model fitting process continued until all critical variables and their interactions were used in the models.

Finally, for the sub-samples where two-way interactions were significant, a generalized linear model (GLM) was used to help decide which interaction/combination to keep and which to collapse. The generalized linear model had the as its form: $g(y_i) = x_i^{'}\beta + \varepsilon_i$ Where $g(y_i)$ is the link function; x_i is a column vector of the explanatory variables for observation i; β is vector of coefficients; and ε_i are assumed to be independent normal random variables with zero mean and constant variance. In this application, an identity link function is used, that is $g(\mu) = \mu.$ x_i could be one or more of the four critical variables and/or their interactions.

The result of this recursive series of ANOVA and final GLM was a total of 96 respondent groups (i.e., nodes). Within each node respondents share homogenous characteristics in terms of the total number of magazines read thereby reducing the within cell variance. A graphical display of the tree can be found below in Figure 2.

Figure 2



[2] The 4-factor ANOVA model had the standard form of: $\mu_{i,j,k,l} = \mu_{....} + gender_i + origin_j + segment_k + region_l + \text{int } eractions + \varepsilon_{i,j,k,l}$ Where μ is an overall mean, gender i is the effect of level i (i = 1, 2) of the factor gender, origin j is the effect of level j (j = 1, 2) of the factor origin, and so on. The interactions include all possible interactions among all factors (i.e. 2-way, 3-way, and 4-way).

Distance Metrics

Two different distance metrics were evaluated: Euclidean distance and Mahalanobis distance. For the Euclidean distance, we addressed scale differences by first recoding all variables to have the same range of 1. The Euclidean distance is defined as follows:

$$d = \sqrt{(x-y)^T (x-y)}$$

And the Mahalanobis distance is defined as:

$$d = \sqrt{(x-y)^T \Sigma^{-1} (x-y)}$$

Where T denotes the transpose of the vector and Σ^{-1} is the inverse of the covariance matrix of the non-critical variables estimated using all respondents from both the online and the offline for a given subgroup.

Results

While we evaluated each of the fusion approaches and the distance metrics sequentially we will simply summarize our evaluation of the distance measures first before presenting our primary results.

Effect of Distance Metrics:

To determine which distance metric was most effective in selecting the nearest donor match, we compared the percent "read" versus "not read" during the past six months for each of the 135 magazines.

For Approach 1, analyses were conducted at the respondent level and for each magazine. We applied each of the two distance metrics to the dataset. If both measures yielded a corresponding "Yes" or "No," it was defined as a match. Otherwise it was not a match. Overall, 96% of the fused results matched between the two distance metrics.

For Approach 2, (Constrained), it is impossible to evaluate at the respondent level since each respondent was fused with fractions of respondents. The incidence of magazine readership was therefore evaluated as the absolute difference incidence rate obtained for each magazine. The mean absolute difference across all 135 magazines was about 0.1% indicating a high degree of consistency.

These findings indicate that the effect of distance metrics is very small. Since most fusion experts we consulted and found in the literature currently set the Mahalanobis distance measure as a standard, we applied this metric to our fusion efforts.

Fusion Success Criteria

To determine the success of our approaches, we applied a series of assessment criteria. First, within each approach we tested the reliability of our fusion via the standard spilt sample technique. Next, we compared the AIA (Average Issue Audience) measures of our fusion efforts to that of actual data from respondents. Finally, we conducted a validation study in which a portion of the OMS respondents were surveyed again with the OMR questionnaire through postal mail. A total of 2,461 OMS respondents completed the OMR survey. This assessment was used as our primary criteria for fusion effectiveness and the results of which are discussed below.

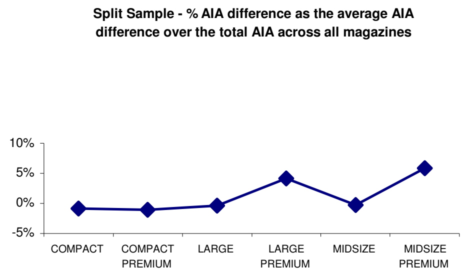
Validation Results

We examined the fusion effectiveness in two ways: percent match at the respondent level between the actual response and the fused data for each magazine; and how well the fusion preserves the AIA.

Approach 1 and Approach 2 resulted in an average of 87% match across all magazines with a range from 54% to 97%. This is slightly better than the theoretical number based on probability estimate and no fusion is applied.

For Approach 2, we calculated AIA for each magazine using the actual responses and the fused data. A difference is calculated and then expressed as the percent of the total AIA from the OMR. Graph 1 below displays the difference by vehicle super segment. The difference is relatively small.

Graph 1

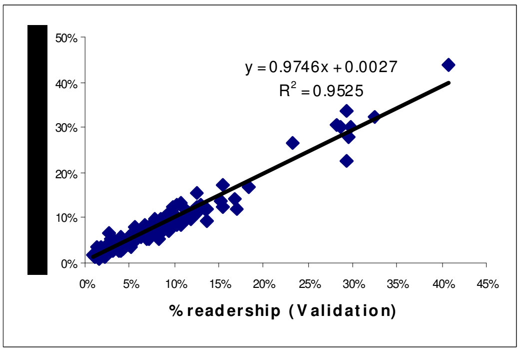


Approach 1 (Unconstrained) vs. Approach 2 (Constrained):

To evaluate the effectiveness of Unconstrained and Constrained fusion approaches, we compared the fused data to the validation data across each magazine. For each magazine we assessed whether a respondent had or had not read it in the past six months. We then compared this stated readership measure to that of our fused estimate. A percentage match was then calculated for each of the 135 magazine for both the Constrained (Approach 2) and Unconstrained (Approach 1) approaches.

As displayed below, the R^2 of the readership incidence between the validation data and the fused data is 0.95 for Approach 2. (Not displayed is the model fit for Approach 1 which was R^2=0.94). The scatter plot between the validation data and the fused data for Approach 2 indicated a good fit across all respondents at the fused and actual readership levels (see Graph 2 below).

Graph 2



We then examined the relative differences between the fused data to those from validation study where we obtained actual readership rates for each magazine and compare the accuracy of both Approaches 1 and 2 separately. Table 2 below shows the average difference of the percent readership across 135 magazines between the fused data and the validation data. Approach 2 appears to be slightly better and the overall results look very good.

Finally, while most users of the data will not need to make decisions at the level of an individual reader, we examined the level of accuracy at the aggregate level. Table 3 shows the average percent match across all 135 magazines. Both approaches show improvement over the baseline, which is the expected percent match based on the reported percent readership.

Table 2

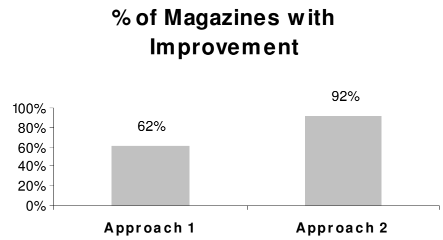
	Approach 1	*Approach 2*
Mean	0.4%	-0.1%
Std	1.9%	1.6%
Median	0.4%	-0.1%

Table 3

	Approach 1	*Approach 2*	**Baseline**
Mean	86.6%	86.8%	86.0%
Min	53.9%	53.7%	50%
Max	97.0%	97.4%	97%

At the individual magazine level, the percent of magazines with improvement of percent match at respondent level over the baseline is 62% for Approach 1 and 92% for Approach 2. As can be seen, Approach 2 (Constrained) is much better than Approach 1 in this respect (see Graph 3).

Graph 3



There are several reasons for the limited accuracy at the respondent level. First, there was a time lag between the OMS and the validation study. To the degree to which there is seasonality in an individual's web site visitation pattern this effect will account for some variation in the data. Second, the matching variables used for this fusion were not fully predictive of all magazines. Hence, the level of predictability was minimized. Third, individual level error rate may account for some differences.

In summary, the difference between Approach 1 and Approach 2 was relatively small but favoring Approach 2. Of greater importance, however, Approach 2 (Constrained) has the advantage of preserving the AIA (Average Issue Audience) at various levels of analyses.

Approach 2 vs. Approach 3:

As indicated earlier, the difference between Approaches 2 and 3 was that of the selection of critical variables. For Approach 3, we increased our accuracy by statistically deriving sub-samples for matching. This allowed the level of classifications to vary from one sub-sample to the other and it was more dynamic in a sense rather than static. The Table 4 below illustrates the improvement from Approach 2 (Constrained) to Approach 3 (Dynamic Constrained).

Table 4:

JD POWER 2007 FUSION STUDY

Comparing Fusion Model Results to Media Study (OMR)

Approach 2 (Constained)

	INDUSTRY			TOYOTA			CHEVROLET		
	Fusion	Media	Difference	Fusion	Media	Difference	Fusion	Media	Difference
TIME	1,988,138	2,022,437	1.7%	263,938	288,096	8.4%	225,845	198,514	13.8%
Reach %	*16.0%*	*16.3%*	*0.3%*	*16.6%*	*18.1%*	*1.5%*	*14.5%*	*12.8%*	*1.8%*
Sports Illustrated	1,657,094	1,579,469	4.9%	172,317	164,039	5.0%	246,726	209,183	17.9%
Reach %	*13.4%*	*12.7%*	*0.6%*	*10.8%*	*10.3%*	*0.5%*	*15.9%*	*13.4%*	*2.4%*
Fortune	688,785	763,119	9.7%	94,386	106,227	11.1%	64,438	72,023	10.5%
Reach %	*5.6%*	*6.2%*	*0.6%*	*5.9%*	*6.7%*	*0.7%*	*4.1%*	*4.6%*	*0.5%*
Money	462,866	500,079	7.4%	55,250	61,808	10.6%	45,701	49,326	7.3%
Reach %	*3.7%*	*4.0%*	*0.3%*	*3.5%*	*3.9%*	*0.4%*	*2.9%*	*3.2%*	*0.2%*

Approach 3 (Dynamic Constrained)

	INDUSTRY			TOYOTA			CHEVROLET		
	Fusion	Media	Difference	Fusion	Media	Difference	Fusion	Media	Difference
TIME	2,010,204	2,022,437	0.6%	283,058	288,096	1.7%	198,646	198,514	0.1%
Reach %	*16.2%*	*16.3%*	*0.1%*	*17.8%*	*18.1%*	*0.3%*	*12.8%*	*12.8%*	*0.0%*
Sports Illustrated	1,563,576	1,579,469	1.0%	193,826	164,039	18.2%	197,386	209,183	5.6%
Reach %	*12.6%*	*12.7%*	*0.1%*	*12.2%*	*10.3%*	*1.9%*	*12.7%*	*13.4%*	*0.8%*
Fortune	763,831	763,119	0.1%	111,562	106,227	5.0%	68,045	72,023	5.5%
Reach %	*6.2%*	*6.2%*	*0.0%*	*7.0%*	*6.7%*	*0.3%*	*4.4%*	*4.6%*	*0.3%*
Money	499,825	500,079	0.1%	68,352	61,808	10.6%	40,550	49,326	17.8%
Reach %	*4.0%*	*4.0%*	*0.0%*	*4.3%*	*3.9%*	*0.4%*	*2.6%*	*3.2%*	*0.6%*

Dynamic One to One by segment (illustrating improvement over make level analysis)

	COMPACT BASIC			MIDSIZE CUV			LARGE PICKUP		
	IMPT	Media '07	Difference	IMPT	Media '07	Difference	IMPT	Media '07	Difference
TIME	23,609	23,829	0.9%	62,682	62,247	0.7%	220,846	229,184	3.6%
Reach %	*15.4%*	*15.5%*	*0.1%*	*18.2%*	*18.1%*	*0.1%*	*12.4%*	*12.9%*	*0.5%*
Sports Illustrated	12,268	12,821	4.3%	36,040	35,043	2.8%	275,394	289,328	4.8%
Reach %	*8.0%*	*8.3%*	*0.4%*	*10.5%*	*10.2%*	*0.3%*	*15.4%*	*16.2%*	*0.8%*
Fortune	2,786	2,972	6.3%	15,179	14,823	2.4%	42,655	46,004	7.3%
Reach %	*1.8%*	*1.9%*	*0.1%*	*4.4%*	*4.3%*	*0.1%*	*2.4%*	*2.6%*	*0.2%*
Money	4,920	5,395	8.8%	26,957	25,790	4.5%	76,574	78,332	2.2%
Reach %	*3.2%*	*3.5%*	*0.3%*	*7.8%*	*7.5%*	*0.3%*	*4.3%*	*4.4%*	*0.1%*

This confirmation allows the media planners and advertising community to make planning decisions knowing that the data does not contradict any analysis that may be generated separately in the existing OMR and OMS studies for a single magazine or web site. Often times, these two separate studies will be used to build the positioning story along with the IMPT (fused) data. This may be utilized to highlight the contribution of the individual pieces as it relates to the various measured variables in the study. An example of this type of application follows the case study described below.

Case Study

With the application of fusion media planners and publishers can begin to do the following:

- apply Purchase Funnel metrics directly to media brands,
- track growth and shifts in the marketplace for each medium, including print and online,
- quantify overall delivery against key consumer, automotive brand and segment targets,
- determine similarities and differences between print and online components and measure the impact of the combination, and
- provide additional substantiation to support multi-platform buys and programs

Positioning Brands with the Fusion Model

The first step in the planning process is to evaluate the differences in audience coverage generated by the IMPT (fusion model) vs. the existing research for media brands (OMR). The ability to minimize the differential between the model and existing research provides the advertising community with confidence that the model mirrors the behavior of new vehicle buyers from a study which has already been accredited by the industry.

The most important application of the fusion model is to determine the total reach between a brand's print and online audience. This approach is one that many subscribing brands will use to demonstrate impact and delivery and one that certainly will be evaluated by the media community. Table 5 highlights a more straightforward single brand combination against the total base of new-vehicle buyers. Numerous combinations of magazines and online brands can now be put together in the current model. The combination of multiple brands (print and online—including portals and non-magazine sites) reflects the realities of the planning process and the marketplace.

Using TIME magazine as an example, the data shows that the magazine delivers over 16% of all new-vehicle buyers, while TIME.com reaches over 5% of the market. Together the two deliver over one-fifth of consumers which demonstrates the reach impact that the brand has in the new-vehicle marketplace.

Table 5:

J.D. Power and Associates 2007 W1 Integrated Media Planning Tool

	Print	**PRINT ONLY**	Online	**ONLINE ONLY**	**DUPLICATION**	**NET**
TIME/TIME.com	2,010,204	**1,893,104**	666,811	**549,711**	**117,100**	**2,559,915**
Reach %	16.4%	**15.4%**	5.4%	**4.5%**	**1.0%**	**20.9%**

Now, one can build the argument about the importance of communicating with new-vehicle buyers across all stages in order to affect vehicle brand selection—since this brand delivers almost one-quarter of the market at the acquisition stage. As noted earlier, the purchase funnel shows that consumer magazines and the internet were primary sources of information for much of the purchase path.

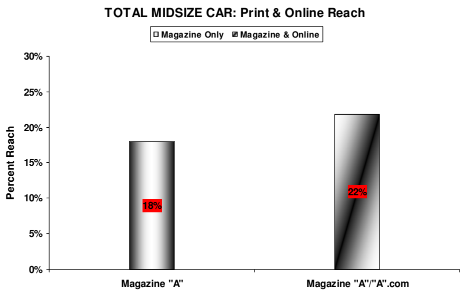
In addition, since the duplication is low (1.3%), positioning the brand in this fashion demonstrates the additional reach the combination delivers across the funnel.

Additional Positioning

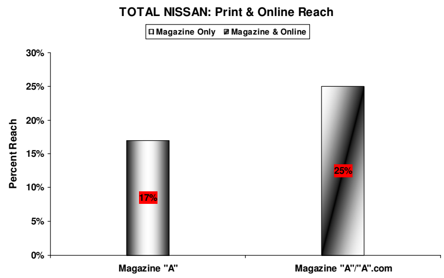
The richness of the data allows the media community to take the information to the next level. While we were able to highlight the impact that the combination of print and on-line has against new-vehicle buyers, very often the need to build a story within a vehicle segment or brand arises.

Using midsize cars as an example demonstrated how online contributes to the reach of this target by adding 5 reach points (see Graph 4). The impact of the combination of print and online is also demonstrated at the brand level by increasing the reach by 8 points (see Graph 5).

Graph 4:



Graph 5:



Finally, using the combination of print and online reach estimates also provides can be used to generate costs efficiency which can be applied competitively against other media combinations

Conclusion

Media publishers are especially interested in this new data technique because it allows them to suggest media plans to clients that include all of their properties, or even combinations to compliment properties already being purchased by clients. By pulling the data together into a single data base at the respondent level, it is possible to measure net reach across multiple platforms helping media planners and advertisers to determine the most efficient way to plan a media buy. Selecting media separately for each of the different platforms does not allow the media planner or advertiser to take advantage of synergies between platforms to increase frequency of advertising exposure. Nor, does it permit any of the parties involved the opportunity to increase net reach, not just among magazine readers (for example), but across all media in which consumers engage.

References

Schoell & Guiltinan (1992) Marketing: Contemporary Concepts and Practices.

Soong, R (2001). The Anatomy of Data Fusion. 2001 Worldwide Readership Symposium (Venice).

Napior, D & Mattlin, J (2005) Calibrated Fusion Evaluation: The MRI-Comscore Case. Worldwide readership Symposium 2005 (Prague)

Collins, J. & Pingitore, G (2007). Dynamic Segmentation Fusion. Worldwide readership Symposium 2007 (Vienna)