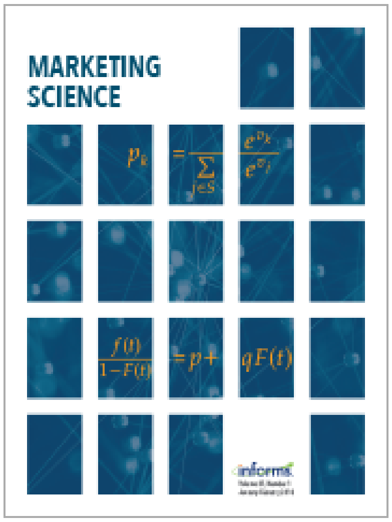


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# Practice Prize Paper—Implementing Integrated Marketing Science Modeling at a Non-Profit Organization: Balancing Multiple Business Objectives at Georgia Aquarium

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## Practice Prize Paper

# Implementing Integrated Marketing Science Modeling at a Non-Profit Organization: Balancing Multiple Business Objectives at Georgia Aquarium

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Georgia Aquarium (GA), a non-profit organization, is the world's second largest aquarium (by water volume) and is among the most popular tourist destinations in the United States. Recently GA management has observed that the organization's growth trajectory is stagnating. While other aquariums face a similar trend, GA wants to be proactive and reverse this direction. They face a multifaceted business challenge involving four conflicting objectives: (1) How to increase revenues without increasing ticket prices; (2) how to increase attendance without compromising visitor satisfaction; (3) how to increase the impact of media investments without spending more; (4) how to attract customers with long-term value potential. To address these challenges, we developed an integrated approach consisting of multiple marketing science models including Data Envelopment Analysis, Competition Analysis, Spatial Analysis, Media Optimization Analysis, and Pass Holder Lifetime Net Revenue Analysis. Based on the findings of our analyses and the parameter estimates of our models, GA proceeded with a field implementation to validate our suggestions. As a result, they realized a 10% increase in attendance and a 12% increase in revenue in 2013, thereby enhancing their bottom line and growth.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0932.

*Keywords*: non-profit; data envelopment analysis (DEA); media optimization; pass holder lifetime net revenue (PLNR); effective media, media spend; type II Tobit model; linear regression model; spatial analysis
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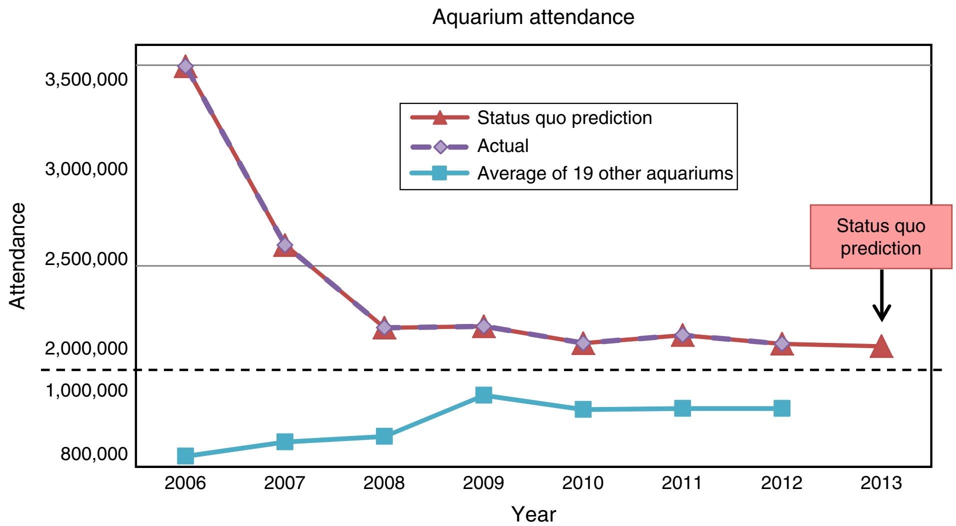
## 1. Introduction

Founded in 2005, Georgia Aquarium (GA), a non-profit organization, is the world's second largest aquarium (by water volume), housing more than 120,000 animals, and representing more than 500 species in about 8.5 million gallons of water.[1] GA has 60 different habitats with about 12,000 square feet of viewing windows, and five galleries housing a diverse population of marine animals and a wide variety of fish of all sizes.

Since its inception, GA has been among the most visited tourist destinations in Georgia, and it continues to be one of the most popular aquariums in the United States. However the GA management team is currently facing a dilemma. Attendance and revenues have been steadily declining (see Figures 1 and 2), and the growth trajectory seems to have stagnated. Revenue for GA comes from two sources: visitors and annual pass holders. To increase revenues, GA can

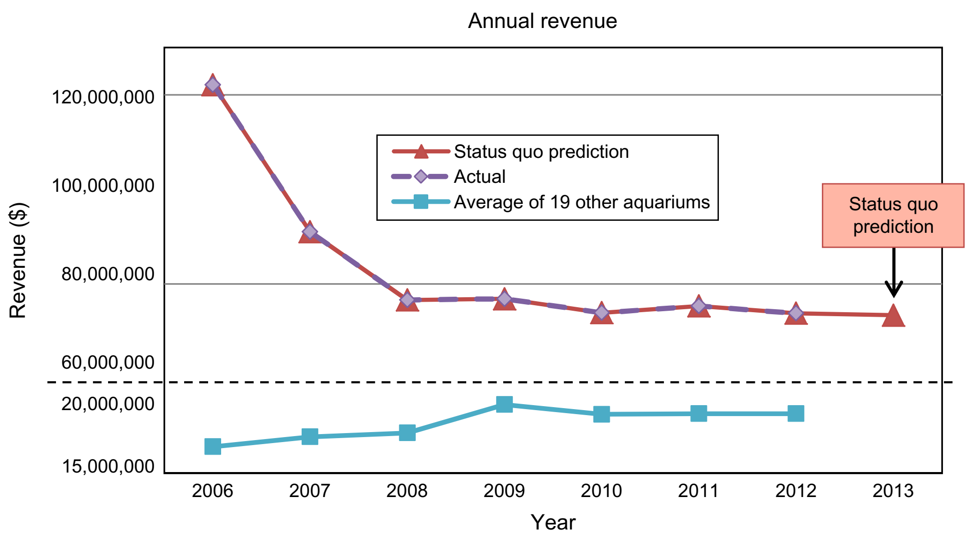
[1] http://www.amusingplanet.com/2013/03/georgia-aquarium-largest-aquarium-in.html.

**Figure 1** (Color online) Performance of Aquariums in terms of Annual Attendance




*Note.* Chart is truncated at the dotted line.

**Figure 2** (Color online) Performance of Aquariums in terms of Annual Revenue

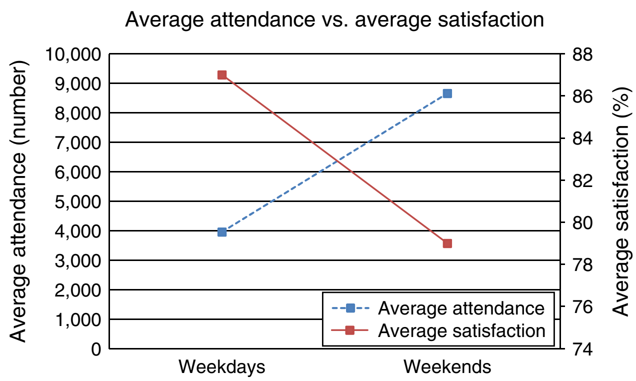



*Note.* Chart is truncated at the dotted line.

focus on increasing new and repeat visitors. However, since annual pass holders visit more often and spend more money during each visit, GA needs to focus on increasing the number of annual pass holders as well as the revenue contributions from them (i.e., via membership fees and spending at the GA Gift Shop and Café). This is a challenging task as the GA management team begins a detailed evaluation of its performance with respect to attendance and revenues.

While examining the general decline in attendance and revenues as shown in Figures 1 and 2, GA management begins to question whether their situation is unique in the industry. Are other aquariums in the country fairing any better? In other words, are all aquariums facing revenue growth pressures and, if so, should GA be taking action to reverse the trend? One of the ways GA can increase their revenues is by increasing ticket prices. However, this is not an option the management team wishes to consider at the moment, given that GA ticket prices are already higher than those of other U.S. aquariums. Instead, GA management wishes to explore ways to increase attendance. Yet there is a problem: Attendance is negatively correlated to satisfaction as shown in Figure 3. Thus, with every attempt to increase attendance, management runs the risk of decreasing overall customer satisfaction. Therefore, the challenge is to determine whether attendance can be increased without compromising overall visitor satisfaction, and whether this is a realistically feasible goal.

**Figure 3** (Color online) Relationship Between Average Attendance and Average Satisfaction ($t-1$) of the Visitors (During 2009–2012)




*Note.* Average visitors' satisfaction is measured at $t-1$.

## 2. Background

### 2.1. Study Context

The finer issue that GA management is eager to address is what they can do to bring more people to the aquarium while staying within the constraints of their existing media budget. They also wish to determine whether their media budget is justified, and if so, whether they are spending it in a way that attracts the right geographical audiences. In addition, they want to know if rival attractions such as the World of Coca-Cola (i.e., the Coca-Cola Museum) and the Atlanta Braves baseball games (i.e., Braves) lend synergies or, instead, have a negative effect on GA attendance and revenues.

This raises an interesting point in the GA life cycle. Management faces a multifaceted business challenge involving multiple, yet constantly conflicting, objectives. This, in turn, creates several other challenges.

- *Challenge* 1: *How can GA increase its revenues without increasing ticket prices*?
- *Challenge* 2: *How can attendance be increased without compromising visitor satisfaction, although attendance is negatively correlated with satisfaction*?
- *Challenge* 3: *How can GA media investments be made more effective, without actually spending more*?
- *Challenge* 4: *How can GA attract customers who are likely to return, and who will be valuable when nurtured in the long run*?

### 2.2. Study Objectives

To address these challenges, we develop an integrated approach composed of multiple marketing science models to provide recommendations to GA for increasing visitors' revenues, attendance, pass holders' lifetime net revenues (PLNR), and overall visitor satisfaction. Our approach is unique in that it not only involves multiple marketing science models seamlessly working together but also uses information from every stage of the analysis to develop truly holistic recommendations. Moreover, the development and implementation of a solution to the GA's business challenges is particularly distinct because GA is a non-profit, service-based organization whose ultimate objective is to optimize visitor satisfaction and experience while increasing long- and short-term attendance and revenue.

We begin by crystallizing the GA's business challenges into four key research questions:

(1) *Is GA efficient in generating attendance and revenue compared to other U.S. aquariums, or is there room for improvement*?

(2) *Who are GA's most valuable annual pass holders, and what are the geographic sources from which similar prospects can be acquired*?

(3) *If attendance needs to be increased, what are the most effective media and geographic sources for acquiring new visitors and annual pass holders*?

(4) *What would be the optimal media spending across online and offline channels to increase attendance and revenues without compromising visitors' satisfaction*?

We develop a five-pronged approach (see Figure 4) to address each of these questions and the statistical tools to answer them.

In the following sections we discuss in detail the first four phases of our implementation process as shown in Figure 4. Next, we discuss implementation of our recommendations by GA. We then explain the impact of our research on GA performance. Finally, we list the key accomplishments of this study, discuss its limitations, and suggest avenues for future research.

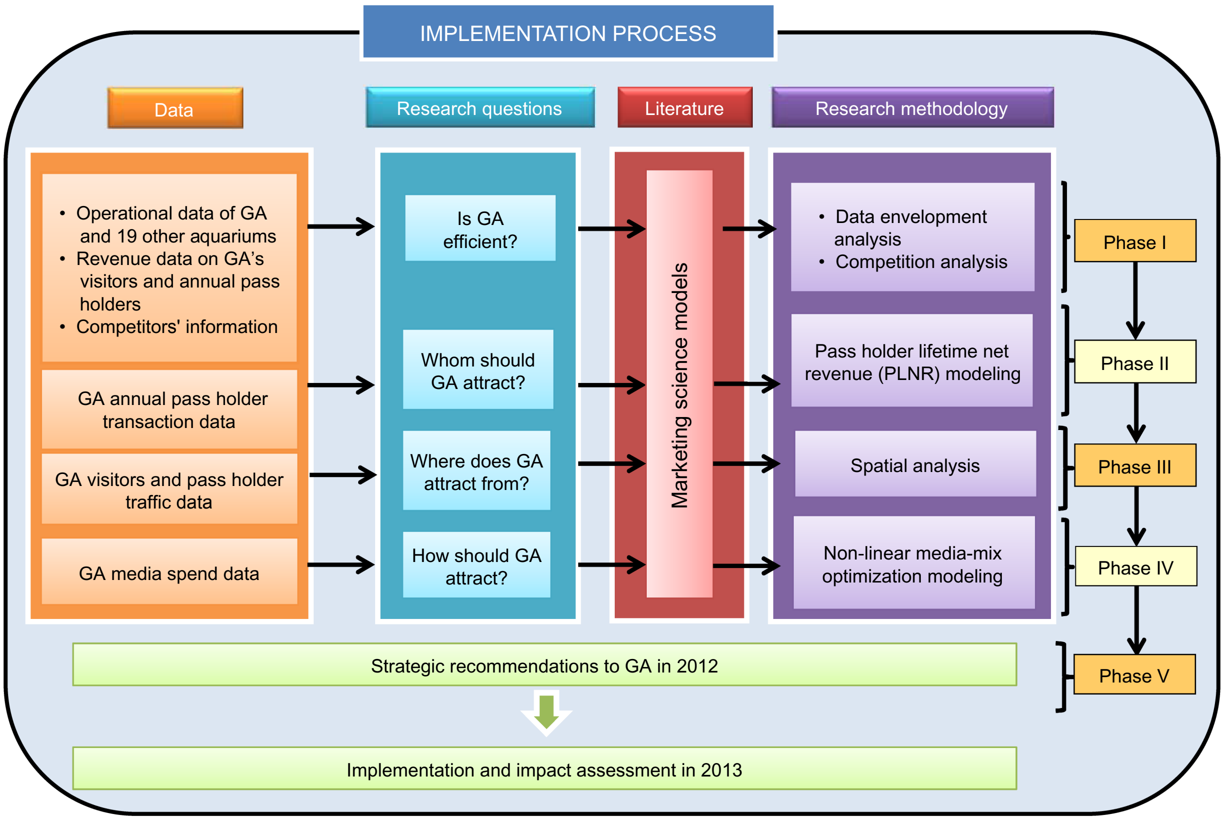
## 3. Research Methodology

### 3.1. Phase I: Measuring the Relative Efficiency of GA

We begin our analysis with an evaluation of the relative efficiency of GA as measured against 19 competing aquariums, based on its existing resource allocations through tools such as (a) Data Envelopment Analysis (DEA) and (b) Super-Efficiency DEA (see WA[2]-F1). The related literature and technical details of DEA and Super-Efficiency DEA, and the efficiency scores of 20 aquariums are available in WA-A1, WA-A2, WA-A3, WA-A4, and WA-T1. The results of DEA and Super-Efficiency DEA confirm that GA is super-efficient in using its input resources to produce output (i.e., attendance and revenue). Because changing input resources is not an option for GA, it must implement alternative strategies to increase attendance and revenue (see WA-F1).

[2] WA indicates Web Appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0932).

**Figure 4** (Color online) Implementation Process




**3.1.1. Competition Analysis.** Our biggest challenge is to increase attendance and revenue through new avenues, even though GA is already super-efficient in terms of generating attendance and revenue. To identify untapped market potential, we evaluate potential competitive effects against other "edutainment"/recreation providers that operate in the same geographical location. Through correlation analysis between GA and competitors' attendance, we identified a competitive synergy with the World of Coca-Cola (Correlation coefficient = 0.89 (<0.001)), and with the Atlanta Braves baseball games (Correlation coefficient = 0.56 (<0.001)). The goal is to increase GA foot traffic through promotional collaborations with these two attractions.

## 3.2. Phase II: PLNR Computation and Sourcing New Pass Holders

As a next step in Super-Efficiency DEA and competition analyses, GA should identify its most valuable annual pass holders, and target similar prospects to increase attendance. We examine the true long-term value of existing GA annual pass holders by analyzing the forward-looking PLNR metric.

**3.2.1. PLNR Modeling Framework.** To predict the PLNR of each pass holder, we adopt the customer lifetime value (CLV) framework suggested by Kumar et al. (2008). We define the PLNR for pass holder $i$ as the net present value of revenue she provides over a three-year period (36 months).

**Model 3a: PLNR Computation**

$$\text{PLNR}_{iT} = \sum_{t=T+1}^{T+3}\left[\frac{p(\text{Repurchase}_{it}=1)\cdot(\widehat{\text{Net Revenue}_{it}})}{(1+r)^{t-T}}\right],$$

where,

$\text{PLNR}_{iT}$ = Lifetime net revenue for pass holder $i$ at time $T$;
$p(\text{Repurchase}_{it})$ = Predicted probability that pass holder $i$ will repurchase the pass in time $t$;
$\widehat{\text{Net Revenue}_{it}}$ = Predicted net revenue from pass holder $i$ at time t;
$t$ = Index for time period, year in this case;
$T$ = Marks the calibration or observation of time frame;
$r$ = Yearly discount factor, 0.12 in this case (as provided by the firm).

The computation of PLNR is based on two factors: (a) the probability that a pass holder would repurchase his pass in each time period ($p(\text{Repurchase}) = 1$ in Model 3a), and (b) the net revenue (in \$) provided by the pass holder in each time period ($\widehat{\text{Net Revenue}}_{it}$ in Model 3a). GA defines a pass holder as an individual who purchases the pass at least once in her lifetime. For example, a person who has purchased the pass but who may or may not subsequently repurchase is a GA pass holder. Although a pass holder could purchase a pass in one year and repurchase after a gap of a few years, here we model the probability of repurchase for each pass holder for each year.

**3.2.2. Data, Modeling Time Line, and Model Specification.** GA provided us with transactional data for five years from January 2008 to December 2012 (see WA-F2) for model development, estimation, and validation. This data consisted of revenue from pass sales, revenues from the gift shop and café, and demographic information such as age, the number of people in a household, and the time of purchase/repurchase of the passes for each pass holder. We use the data from the first three years (January 2008 to December 2010) to predict pass holder behavior in the fourth year (January 2011 to December 2011). We then use the 2009–2011 data and the model estimates to predict pass holder behavior in 2012. To validate the model, we compare the 2012 predictions from our model with actual 2012 data. Based on the available data, we define several variables to be used in the PLNR computation (see WA-T2).

To calculate the pass repurchase probability ($p(\text{Repurchase}_{it} = 1)$), we specify a probit selection model where repurchase probability is modeled as a function of a set of variables for each pass holder in each year as shown in Model 3b. The data is cross-sectional where each pass holder has one observation to model the two PLNR components.

**Model 3b: Calculating Pass Repurchase Probability Using the Probit Selection Model**

$$p(\text{Repurchase}_{it} = 1 \mid X_{it}) = \Phi(X'_{it}\beta).$$

The link function in Model 3b indicates cumulative standard normal probability distribution. For each pass holder, the observed information is captured by vector ($X_{it}$). The vector of unobserved variables ($\text{Repurchase}^*_{it} = X'_{it}\beta + \epsilon_{it}$) is related to the utility difference of two choices (repurchase/not repurchase) (Lechner 1995). The observed dependent variable ($\text{Repurchase}_{it}$) determines whether the pass holder has repurchased the pass such that

$$\text{Repurchase}_{it} = \begin{cases} 1 & \text{if Repurchase}^*_{it} > 0 \\ 0 & \text{otherwise} \end{cases}.$$

We further predict the net revenue that each pass holder will contribute, based on the assumption that she repurchases the pass after incorporating the inverse Mills ratio from the probit model. To predict the net revenue for each pass holder, we use a conditional regression model as shown in Model 3c.

**Model 3c: Pass Holder Net Revenue Using Regression Model**

$$\widehat{\text{Net Revenue}}_{it} = \gamma Z_{it} + \varepsilon_{it}.$$

The specification of $X_{it}\beta$ and $\gamma Z_{it}$, the definition of the variables, descriptive statistics, and correlation among the independent variables are available in WA-B1, WA-B2, WA-T2, WA-T3, and WA-T4, respectively.

**3.2.3. Model Estimation and Robustness Check.** This section reflects what was actually used in the implementation together with the robustness checks suggested by the review team. We estimate Models 3b and 3c using a type-II Tobit selection modeling framework, which controls for any potential selection bias. In addition, we consider the interaction among different variables in the model to accommodate for the joint effect of two or more variables on repurchase incidence and revenue. To identify the specified econometric model, exclusion restrictions are needed. When assigning predictors in Models 3b and 3c, we ensure that there is at least one unique predictor for repurchase propensity to ensure model identification (Greene 1993). We have used lag of total marketing expenses on each pass holder by GA as the exclusion variable in the selection equation (Model 3b). Because the goal of GA marketing expenditures is re-purchase by pass holders, we believe that lag of total marketing expenses will influence the repurchase probability at "$t$." Net revenue at "$t$" depends not only on the amount paid for the pass but also on the amount spent by pass holders inside the aquarium (at the gift shop and café). Net revenue at "$t$" is calculated as the difference between total revenue from pass holder $i$ at "$t$" and marketing expenses by GA on pass holder $i$ at "$t$." We believe that the lag of total marketing expenses will not have a significant impact on the net revenue as the lag of total marketing expenses does not include pass holder spending inside the aquarium. Furthermore, we found a low correlation (0.17, $p < 0.001$) between net revenue at "$t$" and the lag of total marketing expenses. We observe that the major source of variation in the lag of average annual revenue across pass holders arises from the additional pass holder spending inside the aquarium. Hence, we believe that the lag of average annual revenue will influence the net revenue at $t$. Because the variation in the lag of average annual revenue is not significantly influenced by the pass price paid by the pass holders, we believe that the lag of average annual revenue will not significantly affect repurchase probability. Similar justification is applicable to the lag of average growth in revenue. We also find significant correlation of the lag of average annual revenue and the lag of average growth in revenue with net revenue at $t$.

To check the robustness of our PLNR modeling approach, we also estimated the model using transformed variables.[3] We have used lag of total marketing expenses per visit, lag of average annual revenue per visit, and lag of growth in revenue per visit in place of the original exclusion variables. Furthermore, Models 3b and 3c are also jointly estimated with "Craggit" procedure (Burke 2009) in STATA, which relaxes the exclusion restriction, using the original variables.

The model estimates and performances with the transformed variables (see WA-T5 for the parameter estimates) are similar to that of the original model estimates and performances used for the PLNR computation. This illustrates the robustness of our implemented PLNR model. The small difference between our estimates from the joint estimation and the original estimates stems from the possible biases in the two-step estimation in the type II Tobit model.

**3.2.4. Model Validation and Model Comparison.** Using the estimates of the model for the 2008–2010 data and the 2009-2011 data, we make predictions for 2012. We then compare actual 2012 data with our model-based predictions. We find the HIT rate and the mean absolute percentage error (MAPE) as shown in WA-T6 and WA-T7 confirming the excellent fit of the model.

Furthermore, to verify the performance of our model, we compare it with a benchmark model, not including interaction effects. The fit of our final jointly estimated model with the interaction effect is better than the fit with the benchmark model. Hence, for prediction, we use the jointly estimated model that incorporates the interaction effect.

**3.2.5. Model Based Prediction and PLNR.** Based on the model, we predict pass repurchase probability for pass holder $i$ at time $t$ and the net revenue contribution for pass holder $i$ at time $t$ if the pass holder repurchases the pass for 2013. To do this we use the 2010–2012 data and the model parameter estimates. We then prepare a "One step ahead" forecast for 2014 and 2015 and find the PLNR score of each pass holder. Pass holders were rank-ordered based on their PLNR scores (see WA-F3), and then categorized into five segments: Super-high PLNR, high PLNR, medium PLNR, low PLNR, and very low PLNR.

GA management wanted to know the lifetime net revenue of its pass holders, and to identify the drivers of high PLNR. To identify these drivers, we followed the approach of Reinartz and Kumar (2003) (see WA-T2). The various exchange characteristics that we included as drivers of PLNR are: the average revenue from each pass holder, the repurchase frequency, the most recent purchase, the frequency of use, the average interpurchase time, the past average purchase activity, and the expenditure incurred by GA in managing each pass holder. Pass holder heterogeneity was captured by two variables: the age of the pass holder and the number of people in the household. We have identified the retention rate (see WA-F4) and recommended segment-specific retention strategies (see WA-T8) to minimize churns. GA adopted our recommended retention strategies, and as a result, realized a 10% (HBR 2015) increase in pass holder retention levels. In the interest of further managerial relevance, we advised GA on the behavioral indicators of a high PLNR pass holder (see WA-F5). We advised GA to monitor these drivers on a dashboard to see how they could improve scores on each driver.

### 3.3. Phase III: Integrated Spatial Analysis

Once we identified the most valuable GA pass holders along with segment-specific acquisition and retention strategies, one question remained: From where could GA attract new pass holders and visitors?

To guide GA in developing effective acquisition and retention strategies, we performed a spatial analysis comparing the top 50 zip codes for visitors' origin, based on traffic, to the top 50 zip codes from where the most valuable (i.e., positive PLNR) pass holders originated, based on lifetime net revenue and traffic. We matched the zip codes from the two categories and found overlap in 40 zip codes. We then defined a demographic profile range for a typical GA visitor in terms of age, marital status, and household income. In analyzing the visitor and pass holder profiles from the 40 common zip codes of origin, we found 10 unique zip codes from where the highest number of positive PLNR pass holders originated, and 10 unique zip codes from where all GA visitors originated (see WA-F6).

**3.3.1. Targeted Zip Codes: Acquisition and Retention Strategies.** Based on the findings of the spatial analysis, we targeted new markets for further acquisition of pass holders and visitors. To achieve this objective, we used the demographic indicators of 40 common zip codes and looked for the zip codes wherein people with similar profiles reside. This cloning exercise generated 39 look-alike zip codes (i.e., new markets) from which GA might acquire new visitors and pass holders.

[3] We thank the senior editor for suggesting the robustness check with the transformed variables. We have found similar estimates with the transformed variables.

*Retention Strategy*: Subsequently, we recommended that GA increases its marketing initiatives in the 40 common zip codes that were identified. In this way, GA could facilitate: (1) lower and more efficient marketing communications spending, and (2) increase effectiveness in targeting and attracting new visitors and pass holders. This increase in efficiency and effectiveness would allow GA to maximize its revenue. Once GA had successfully implemented the marketing efforts in the 40 common zip codes, it could expand its focus by targeting the unique zip codes to reach additional visitors and pass holders (see WA-F6).

*Acquisition Strategy*: After focusing on the 40 common zip codes and the unique zip codes for retention efforts, we recommended that GA implement an acquisition strategy by targeting the "look-a-like" zip codes that we identified. This would allow GA to target and potentially acquire new visitors and pass holders with similar socioeconomic characteristics of the 40 common zip codes (see WA-F6 and WA-F7). We further recommended the ideal media to reach the potential visitors and pass holders from among these look-a-like zip codes.

### 3.4. Phase IV: Media Optimization

Given the identified market potential in the common, specific, and look-a-like zip codes, the next major challenge was converting prospective customers into actual visitors and pass holders. To address this challenge, we evaluated the effectiveness of existing GA marketing strategies, and analyzed its online and offline media plan and budget allocations. Specifically, in this phase we discuss Challenge 3 and research questions 3 and 4. We find that GA has been investing in different media such as radio, TV, newspapers, magazines, outdoor, digital, etc. However, it is not clear whether this media investment is achieving the best possible attendance and revenue results. Therefore, GA wishes to assess the effectiveness of each media type to determine if there is a need to reallocate media investments and optimize its media plan to maximize attendance and revenues. By investing in the right media, rather than simply spending more across the board, GA can optimize its media plan across online and offline channels to boost attendance and revenue.

Extant academic literature has extensively analyzed and quantified the relationship between advertising and sales (in this case "Attendance"), as well as the synergies between online and offline advertising. Literature has also studied the impact of media scheduling on a firm's visibility and sales, and has identified strategies and tactics to enhance the effectiveness of online and offline media efforts. WA-T9 summarizes the findings of select academic literature, and highlights the differential contributions of our study to media optimization.

In the section that follows, we develop and estimate a media optimization model that helps us in recommending media mix strategies for GA to maximize attendance and revenue. In our media optimization model, we bring online and offline media together in a single model and explore their effect on GA attendance.

**3.4.1. Media Optimization Model Development.** To identify the most effective media and their respective effects on GA attendance levels, we evaluate various linear and nonlinear models. Our data consists of monthly GA spending (in $) on each of the media (online and offline), the monthly attendance (in numbers), the monthly attendance of two of its competitors (World of Coca-Cola and Atlanta Braves baseball games), the average satisfaction of visitors, the GA ticket price and changes in the quarterly U.S. GDP for five years. We considered spending in media such as radio, TV, online, outdoor, newspaper, magazine, and other media. As spending on media channels such as taxi tops, bus wraps, direct marketing, conventions, buskings, etc., was miniscule, we took a combined view of spending in all such media and defined it as "other media" in our model.

We began our exercise by developing a multiplicative model as shown in Model 4a. Because GA advertises through more than two media types simultaneously, attendance at time $t$ may be affected jointly by the combination of various media types. To account for such multimedia interactions, we adopt the multiplicative model (Christen et al. 1997, Danaher et al. 2008). The appealing feature here is that this is a log–log model wherein the effects of each media type and other variables are directly evaluated as elasticities.

**Model 4a: Specification of a Multiplicative Model**

$$\begin{aligned}
&\text{GA Attendance}_t\\
&=\exp(\beta_0)\left[\prod_{j=1}^{J}(1+\text{Media}_{jt})^{\beta_j^{Media}}\right][(\text{Ticket Price}_t)^{\beta^{Price}}]\\
&\quad\cdot[(\text{Coke Attendance}_t)^{\beta^{Coke}}][(\text{Braves Attendance}_t)^{\beta^{Braves}}]\\
&\quad\cdot[(\text{Changes in Quarterly GDP}_t)^{\beta^{GDP}}]\\
&\quad\cdot[(\text{Visitors' Satisfaction}_{t-1})^{\beta^{Satisfaction}}]\exp(\gamma_1 D_1)\\
&\quad\cdot\exp(\gamma_2 D_2)\exp(\gamma_3 D_3)\exp(\epsilon_t),
\end{aligned}$$

where,

$\text{GA Attendance}_t =$ Number of visitors at GA at time $t$;

$\text{Media}_{jt} =$ Spend of GA on media $j$ at time $t$ (in $);

Coke Attendance$_t$ = Number of visitors at Coca-Cola museum at time $t$;
Braves Attendance$_t$ = Number of visitors at Braves baseball game at time $t$;
Changes in Quarterly GDP$_t$ = Quarterly growth rate of U.S. GDP from $t-1$ to $t$;
Ticket Price$_t$ = Ticket price of GA at time $t$;
Visitors' Satisfaction$_{t-1}$ = Average satisfaction of visitors at time $t-1$;

$D_1$, $D_2$, $D_3$ indicate the seasonality effect, $\epsilon_t$ is the error term for the model, and $\beta_0$ indicates the intercept of the model. Parameters to be estimated are $\beta_j^{media}$, $\beta^{Price}$, $\beta^{Satisfaction}$, $\beta^{Coke}$, $\beta^{Braves}$, $\beta^{GDP}$, $\gamma_1$, $\gamma_2$, $\gamma_3$. By taking log on both sides, we can obtain the *log–log* model.

In our model, $\beta^{Satisfaction}$ shows how changes in average visitors' satisfaction at $t-1$ affect the GA attendance at $t$; $\beta^{Price}$ provides the price elasticity value. The estimates $\beta^{Coke}$ and $\beta^{Braves}$ capture how the attendance levels at the Coca-Cola museum and Braves games affect GA attendance, respectively. We factored in changes in the quarterly U.S. GDP to capture the effect of the economy on GA attendance through $\beta^{GDP}$. Because spending for media $j$ in some of the time periods is zero, we add 1 to this spending so that the logarithms have feasible values.

**3.4.2. Accounting for Endogeneity.** Endogeneity in sales-response models is common in marketing literature. Marketing mix variables such as media spending suffer from endogeneity issues as explained across extant research (Danaher et al. 2008, Naik et al. 2005). We account for possible endogeneity in our model using the control function approach (Petrin and Train 2010) as demonstrated by Sridhar and Srinivasan (2012) and Gordon et al. (2013), and specifying a model for each media type (see Model 4b).

**Model 4b: Accounting for Endogeneity**

$$(1+\text{Media}_{jt}) = \exp(b_j)\left[\prod_{j=1}^{J}(1+\text{Media}_{jt-1})^{\theta_j}\right] \cdot (\text{GA Attendance}_{t-1})^{\omega_j}\exp(e_{jt}),$$

where,

(GA Attendance$_{t-1}$) = Number of visitors in GA at time $t-1$;
Media$_{jt}$ = Spending in media $j$ at time $t$;
Media$_{jt-1}$ = Spending in media $j$ at $t-1$;
$e_{jt}$ = Residual of the model for media $j$.

We used the log transformation of Model 4b to match the requirement of the final multiplicative model.

**3.4.3. Model Estimation and Results.** We estimate a separate model for each media type and use the residuals of each model as the independent variable in a log–log version of Model 4a. As the endogenous equations have the lag effect of each of the media and attendance, any possible previous period effects have been captured in our model. In addition, as prospects and visitors are exposed to the media every month and our model is at the monthly level, we see no need to consider the carryover media effect. Also, as we considered the seasonality effect in the main model, we do not include it in the endogenous equations.

The final media-mix optimization model is shown in Model 4c where $e_{jt}$ is the residual of the model for media $j$ at time $t$.

**Model 4c: Final Media-Mix Optimization Model**

$$\begin{aligned}
&\log(\text{GA Attendance}_t)\\
&=\beta_0+\sum_{j=1}^{J}\beta_j^{media}\log(1+\text{Media}_{jt})+\beta^{Price}\log(\text{Ticket Price}_t)\\
&\quad+\beta^{Satisfaction}\log(\text{Visitors' Satisfaction}_{t-1})\\
&\quad+\beta^{Coke}\log(\text{Coke Attendance}_t)\\
&\quad+\beta^{Braves}\log(\text{Braves Attendance}_t)\\
&\quad+\beta^{GDP}\log(\text{Changes in Quarterly GDP}_t)+\gamma_1 D_1+\gamma_2 D_2\\
&\quad+\gamma_3 D_3+\sum_{j=1}^{J}\delta_j e_{jt}+\epsilon_t.
\end{aligned}$$

We estimated the final media mix model using *R* in a Bayesian framework. We tested the residuals for any violation of the assumptions and did not observe any significant violation. Our model showed an excellent fit with an *R* square value of 74.87% and MAPE of 1.2%. We then identified radio, TV, online, and magazine (i.e., print) as the most effective media for GA based on the significance level (at 5%) of $\beta_j^{media}$ (see WA-T10). We also found outdoor media to be of least significance, and all other media types to be nonsignificant.

**3.4.4. Benchmark Models and Model Comparison.** To compare the performance of our multiplicative media mix model, we estimated two benchmark models: (a) a linear model, and (b) a linear model with interactions among variables. The linear model has an *R* square of 46.11% and MAPE of 12%. The linear model with interactions has an *R* square of 59.19% and MAPE of 9.08%. We find that the performance of the multiplicative model in terms of MAPE and *R* square value is superior to the benchmark models. Hence, we use the multiplicative model for further analysis.

**3.4.5. Finding the Media Specific Spend.** Once we found the most effective media for GA, we needed to determine efficient media budget allocations. The media budget for 2013 was given to us for optimal allocation. We maximized the following objective function:

$$\text{Max}(\text{GA Attendance}_t).$$

We then strategized media-specific spending using a nonlinear optimization procedure. We set several boundary conditions in the optimization process. We allowed the total spending in each effective media to vary between the maximum and minimum values within the data. Furthermore, we ensured that the sum of the optimal spending in each of the effective media is less than or equal to the GA net media budget (difference between the GA media budget and spending in outdoor media in the previous year). Here, using the parameter estimates of the most effective media and the GA budget constraints, we computed the exact amount that GA should spend on each effective media type, with the exception of outdoor media. We completed our computation by holding other variables constant at their respective mean. GA believes that outdoor media has been helpful in creating awareness among potential prospects. Hence, we recommended that GA maintain its investment at the previous year's level to boost its brand building (although outdoor media is statistically least significant). We also took into account seasonal fluctuations in the observed attendance trends to recommend suitable monthly budget allocations across the year. We solved the resource allocation problem using "nlopte" optimization subroutines in *R* and nonlinear optimization in Excel. Once we established the media-specific investment strategy and budget for each of the effective media, we predicted the attendance and corresponding revenues for 2013. Furthermore, we compared our model-based predictions with existing 2013 predictions which were based on the originally projected media budget. We recommended that GA modify its media scheduling in conjunction with historic trends in foot traffic, and the seasonal peaks and downturns observed at certain times of the year.

GA re-focused its media investments as per our recommendations. Furthermore, as a softer push towards increasing attendance and visitor satisfaction, we recommended a set of onsite engagement strategies and tactics such as better crowd management via streamlining of the traffic flow inside the aquarium, interactive game stations, mascot entertainment, and offsite tactics such as mobile apps. Figure 5 depicts the recommended and actual media investments based on our optimization model.

# 4. Phase V: Quantifying the Overall Impact of Our Models, Analysis, and Strategies

Table 1 depicts the actual results after implementation of our recommendations against our predicted outcomes (based on the assumption that our recommendations would be implemented). In the context of our study, all of the recommendations were implemented for a period of one year. However, the models and the strategies are not time-specific. These results further manifest the substantial, positive impact of our recommendations on the long-term revenues, customer segmentation, and targeting strategies, as well as overall customer experience, perceptions, and satisfaction levels. As further validation of our models and recommendations, the difference between our predictions and actual outcomes was minimal. GA performance predictions for 2013 are shown in column (I) in Table 1. Our model-based predictions for 2013 revenues are shown in column (II), and are based on the budgeted media plan and estimates of the media-mix optimization model shown in Model 4c. Last, columns (III) and (IV) show the actual impact of implementation of our recommended strategies and models.

As demonstrated in Table 1, GA realized a 10% increase in attendance (also see WA-F8) resulting in a 12% increase in revenues (also see WA-F9) in 2013, over the values that were projected for 2013.[4] Also, GA could now quantify the approximate contribution of each media type towards incremental revenues (see Figure 6), and develop future media strategies accordingly. The approximate apportioning of the revenue increases to various media has been identified using standardized model parameter estimates, re-estimated using 2008–2013 data. The field implementation results show that GA could increase attendance and revenue by optimally reallocating their investments toward the most effective media types (*without actually spending more*).

To validate the effectiveness of our modeling approach on GA performance in 2013, we predicted attendance and revenue based on existing media investment strategies for 2013. We then compared these values with those obtained through our recommended media optimization plan. We could foresee a growth of approximately 10%–12% and 12%–14% (based on sampling of the parameter values) in attendance and revenue, respectively, given implementation of our model w.r.t. the baseline predictions that were based on existing media strategy. To ensure the credibility of our results, we confirmed that there was no major event (i.e., games, cultural/educational

[4] https://hbr.org/2015/01/boosting-demand-in-the-experience-economy.

**Figure 5** (Color online) Optimal Investment in Effective Media (Percent Share of Media Spend)

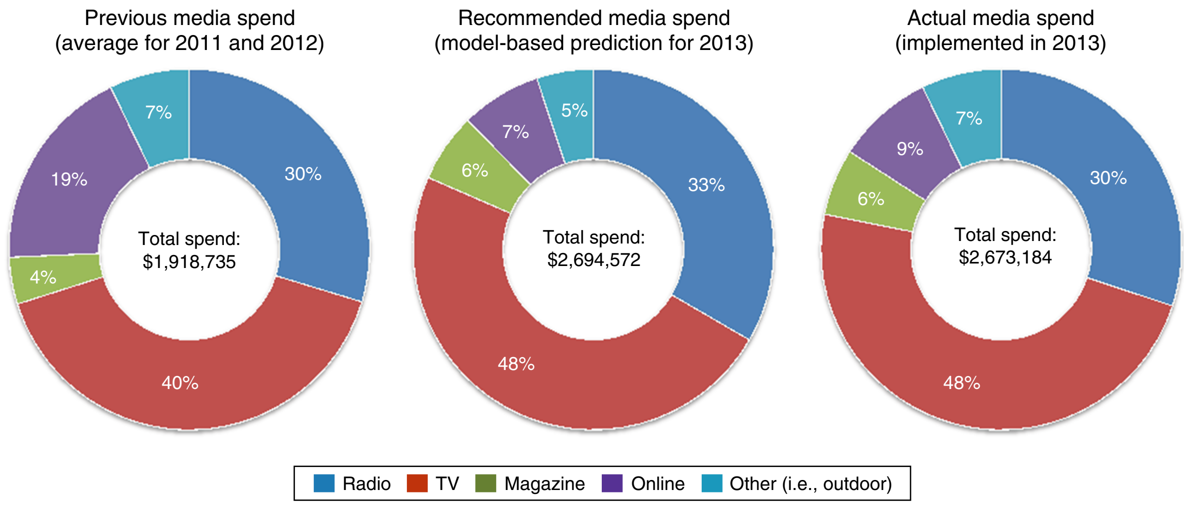
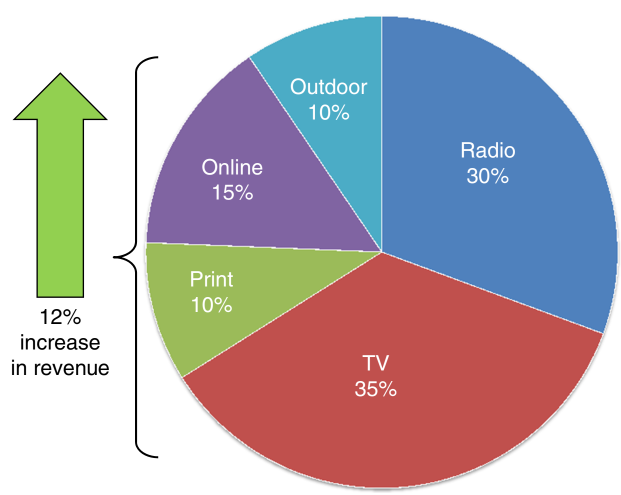



**Table 1** Implementation Results

| Metrics | I: Predictions based on status quo (2013) | II: Predictions based on 2013 media-mix optimization model | III: Actual realization by GA for 2013 | IV: Percentage increase in reality (%) |
|---|---|---|---|---|
| Attendance in nos. (derived from the model) | X | 1.10X–1.12X | 1.1X | 10 |
| Total revenue ($m) measured in terms of attendance · Ticket price + Extra revenue | Y | 1.12Y–1.14Y | 1.12Y | 12 |
| Visitors and pass holder retention (nos.; experienced after implementation of our strategies) | Z | N/A | 1.1Z | 10 |
| Visitors and pass holder acquisition (nos.; experienced after implementation of our strategies) | W | 1.1W | 1.12W | 12 |
| Increase in number of visitors from newly identified zip codes | P | N/A | 1.15P | 15 |

**Figure 6** (Color online) Approximate Percent Contribution of Media to the Increase in Revenue




shows, etc.) in the Greater Atlanta area in 2013, which could have positively affected GA attendance. We were careful to ensure that there were no major additions/special exhibits/new shows at GA in 2013, which could have influenced attendance levels. Furthermore, we controlled for any possible changes in the World of Coca-Cola and Braves games attendance in our model by including them in the model specifications. Moreover, we confirmed the performance of the model to be exceptionally good (with an $R$ square = 74.87%, and MAPE = 1.2%). In reality, the gains experienced by GA in 2013 matched our model-based predictions. GA had successfully ventured deeper into existing and new high potential zip codes that we had identified, armed with the media strategies that we had recommended.

WA-T11 summarizes the other significant results of the implementation of our study, as confirmed by the GA Annual Visitor Survey Report for 2012–2013. This survey showed a 3% increase in overall GA customer satisfaction in 2013 over the previous year. Purchases at the Café and Gift Shop increased by 11% and 8%, respectively. Two particularly encouraging developments were increases in “Entertainment Experience” (5%) and “Likelihood of Returning” (8%)

over the previous year's levels. Another noteworthy impact was the increase in the "Perceived Value" of GA admission price by 7% over the previous year. This metric reflects overall satisfaction levels, and is especially encouraging since it indicates that a higher number of visitors over the previous year consider the experience offered by GA to be well worth the admission price (despite the price being higher than that of other aquariums).

## 5. What Did We Accomplish Through This Study?

The impact of this research can be understood at the firm level as well as at the customer level. At the firm level, the encouraging results from implementation of our research framework prove that it is possible for firms to achieve the right balance between optimizing resources, acquiring/nurturing profitable customers, and maximizing visitor/customer satisfaction. For GA specifically, use of this modeling framework helped its managers evaluate relative operational efficiencies, and confirm that GA was super-efficient. Our framework also helped GA managers to identify the most effective media types, and armed them with marketing strategies to target and acquire visitors as well as nurture valuable pass holders, thereby ensuring significant growth in foot traffic (an increase of 10%) and revenue (an increase of 12%) in 2013.

At the customer level, this study helped GA understand the actual and potential value of its customers, as well as where they come from, thereby facilitating a more customized and effective approach toward retaining its most valuable visitors and pass holders with an average PLNR of $2,065 p.a. (for the most valuable segment), and acquiring similar new prospects. Note also that our approach is future-focused. It helps GA to evaluate current and prospective customers through the lens of future value potential, versus past contributions.

Although this analysis is specific to GA, our framework is scalable and can be applied across all consumer industries, including for-profit firms. This study has armed marketing academia and practitioners with a robust methodology to measure firm efficiency, and to increase attendance and revenues by identifying suitable target markets and media. Our proposed strategies are effective in identifying, acquiring, and nurturing the most valuable members/customers in a measurable, scientific manner instead of relying on a broad-based, mass marketing strategy.

## 6. Limitations and Opportunities for Future Research

Although this paper shows a sound application of marketing science, there are certain limitations, which can be addressed in future research. Our approach was designed to strike a balance between rigor and relevance in terms of implementation. In Phase III, we have not estimated an Integrated Spatial Model. A spatial model can be developed and applied in the future to advance research findings. We have not accounted for the potential endogeneity in the average inter-purchase time (AIT) because of the lack of sufficient data. With more data, the potential for AIT endogeneity could be addressed. With the available data, we also have not found any endogeneity in ticket price, visitors' satisfaction, and attendance at the World of Coca-Cola. However, if such endogeneity is suspected, with additional data over time, future research can account for this potential, and thus enrich the findings.

### Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0932.

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