What is the best way to promote zero calories beverages?

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Introduction

Zero calorie beverages are healthier compared to sugared beverages because they contain less sugar and significantly fewer calories. Over the past decades, hospitals have been striving to promote zero-calorie beverages for a healthier lifestyle. This study employs five interventions to help increase such promotion. These interventions include a 10% price discount, a price discount combined with messaging that explains the reason for the discount, messaging displaying the caloric content in sugared beverages, messaging indicating the amount of exercise needed to burn off the calories in a sugared beverage, and messaging containing both caloric content and the amount of physical activity needed.

The study aims to investigate whether these interventions help encourage people to choose zero calorie beverages over sugared beverages and if such effects varies across hospitals.

Data description and summaries

This is an experimental design where data are collected over 30 weeks, from October 27 to May 23, with a follow-up period of 14 days, gathered from two urban hospitals and one suburban hospital. During this time period, the sales of different types of drinks are recorded (see Table 1).

There are missing entries in this dataset, with a significant portion of the missing data attributed to the 'Juice100,' 'Ojuice,' and 'Sports' columns. Since neither these measurements themselves nor their links with the consumption of ZeroCal/Sugary beverages are the main focus of the study, the missing values in these columns should not be given specific attention. Additionally, there are seven entirely missing consecutive entries at HF hospital during the follow-up period and two isolated cases of missing entries. Such occurrences could be due to public holidays or temporary closures for renovation. In general, such missing data can be classified as missing at random.

Table 1: Summary of data

Data Name	Data Type	Data Description
DofW	Categorical	The day of the week, 7 levels
Site	Categorical	The location of the hospital, 3 levels
Intervention	Categorical	The intervention applied, 9 levels
ZeroCal	Integer	The number of zero calorie drinks sold
Sugary	Integer	The number of sugary drinks sold
Juice100	Integer	The number of Juice100 sold
Ojuice	Integer	The number of Ojuice sold
Sports	Integer	The number of sports drinks sold
Total	Continuous	The sum of all drinks sold

Exploratory Data Analysis

Firstly, to address the influence of location on zero-calorie beverage consumption, which is of primary interest to the study, a spaghetti plot is recommended. A spaghetti plot is typically used to demonstrate the change of multiple flows over time and how they vary across the three sites. Based on Figure 1, it is evident that the time-series data for zero-calorie beverage consumption at the site "chop" are significantly higher than those at the other two sites, suggesting substantial variation in consumption distributions under different interventions. Additionally, the spaghetti plot reveals that except for the initial period at the site "HF," there is no apparent trend at all three sites, as the long-term averages seem to be stable. However, strong weekly variations are evident, implying that it is reasonable to include the day of the week (DofW) and exclude the time (count) in the model.

Formal analysis

This section outlines general strategies for quantifying and comparing the impacts of five different interventions on the consumption of zero-calorie and sugary beverages across three sites.

It is recommended to implement a Generalized Linear Mixed Model (GLMM) to address the problems. A GLMM, an extension of the Linear Mixed Model (LMM) (Winter 2013), can incorporate both fixed and random effects, and also accommodate the response variable being a count variable through a link function (Dobson and Barnett 2018). Specifically, while the fixed effects assess the association of covariates with the response variable across the overall population—serving as a baseline—the random effects account for variations in some associations across different entities or individuals.

In this study, the primary focus is to analyze the effects of the interventions, and therefore, it is suggested to treat the intervention as a fixed effect. Additionally, days of the week should also be considered as fixed effects because they apply to all three sites. To allow for a more

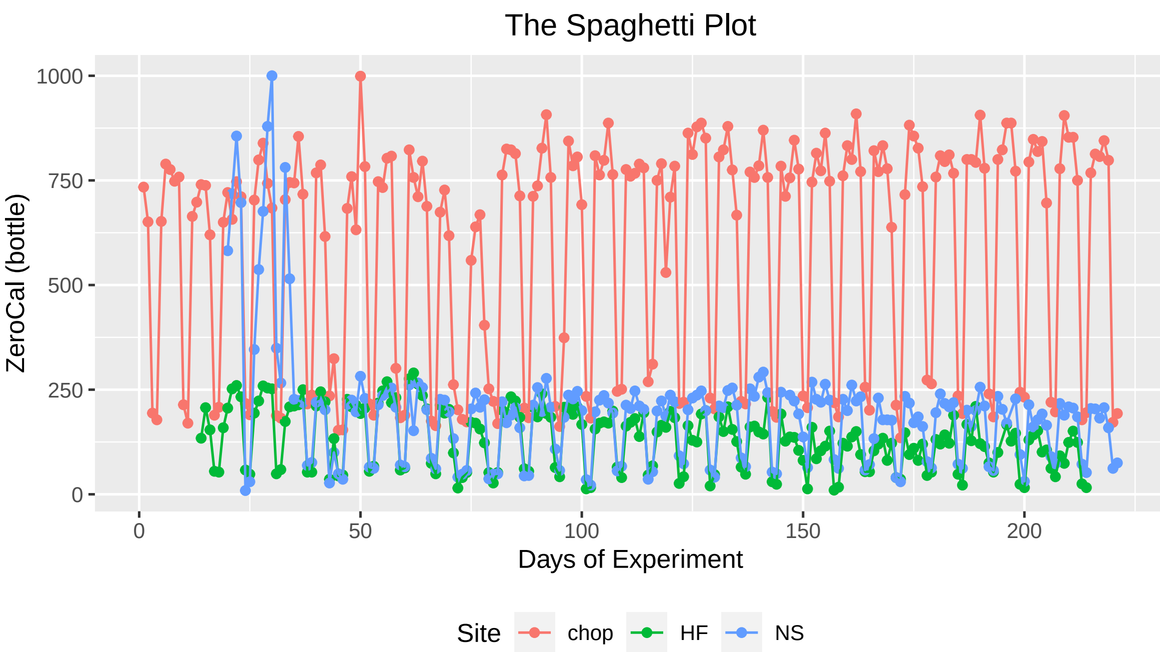

Figure 1: Examples of Recommended EDA Plots

comprehensive understanding of the intervention effects, it is advised to include sites and total as two random effect in the model. These covariates control for variability that might influence the patterns of zero-calorie/sugary beverage consumption. For instance, site differences (which are the secondary statistical question) may impact purchasing behavior due to demographic variations between urban and suburban areas. Similarly, accounting for total daily beverage consumption helps isolate the effect of human traffic on zero-calorie/sugary beverage choices. This comprehensive approach ensures that the analysis accurately reflects the interventions' impact while controlling for external factors. Last but not least, given that the consumption of ZeroCal beverage is count (non-negative integer), it is natural to assume that it follows a Poisson distribution. Subsequently, using an exponential link function to guarantee a positive output from model is suggested.

Hence, the proposed models are

$$ZeroCal \sim Intervention(Site) + DofW + Total$$
$$Sugary \sim Intervention(Site) + DofW + Total.$$

Fixed effects include Intervention, DofW, and Total, while the random effect measures how the effect of Intervention and baseline consumption varies across sites. Note that these models are simplified versions, especially with the omission of the link function. Please refer to the appendix for the formulated models.

However, there are several limitations to the models mentioned above. Firstly, GLLMs do not accommodate autocorrelation in time series data, which refers to the dependence between consecutive observations. Moreover, as mentioned, the model proposed implicitly assumes that the response variables follow Poisson distributions (Coxe, West, and Aiken 2009), where the expectation and variability of response variables should equate, but this assumption can be easily violated in practice.

Conclusions

We recommend using GLMMs to fit the relationship between covariates and response variables. Based on different research interests, response variable should be either ZeroCal beverage consumption or sugary beverage consumption. The fixed-effect explanatory variables suggested are intervention, Total and DofW, and the random-effect explanatory variable is Site.

References

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Statistical Appendix

Mathematical Formulation of Models

Here is a formulation of the Generalized Linear Mixed Model within the context of this research. As suggested earlier, random effects can be placed on both the intervention's slope and intercept. Taking $y = ZeroCal, x_1 = Total, x_2 = Intervention, x_3 = DofW$, the model will take the format of

$$E(y_{ij}) = exp((\beta_0 + b_{0i}) + (\beta_1 + b_{1i} + b_1 x_1)\, x_2 + \beta_2\, x_3 + \beta_3\, x_1) \tag{1}$$

where $b_{0i} \sim N(0, \sigma_1^2)$, $b_{1i} \sim N(0, \sigma_2^2)$ and $b_1 \sim N(0, \sigma_3^2)$. Here, $i \in \{1, 2, 3\}$ is used to index the three sites, and $j \in \{1, 2, \ldots, 221\}$ is used to index the date. σ_1, σ_2 and σ_3 can be estimated using data, and $zero\_calorie_{ij}$ is assumed to have poisson distribution where its expectation should be equal to its variance. When such an assumption is violated, usually quasi-maximum likelihood estimation is used. This method estimates the regression parameters without the need to specify a distribution for the outcome. When such an assumption is violated, usually quasi-maximum likelihood estimation is used. This method estimates the regression parameters without the need to specify a distribution for the outcome.