The Impact of The Amount of Online Advertisements on Governor Walz's Approval Rating by Using Repeated Measures

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Introduction and Background

This is a report commissioned by the Minnesota Governor Tim Walz's campaign office. The purpose of this report is to find out if Walz's online advertisements affect voters. Through this report, the Walz office aims to find out (1) if there are any differences between the first and last approval ratings from participants, (2) whether the amount of online advertisements has a favorable impact on participants, and (3) whether the approval ratings of one month affects next month's approval ratings.

The study investigates whether the amount of online advertisements affects voter's approval ratings of the governor. To investigate this, I used the repeated measures. According to Crowd, "Repeated measure data arises when the same characteristic is measured on each case or subject at several times or under several conditions." (1990) The reason this method is used normally is because repeated measurements of a person or treatment unit occur within-unit correlations over time. It violates the independent assumption of statistical tests. In other words, this method is used to suppress the distortion of independence that occurs when the same unit is repeatedly measured. The given data was measured a total of 12 times a month during a year. By using the repeated measures, I was able to see the change in approval ratings over time.

Mixed effects models were used along with repeated measures. According to Laird, "Mixed effects models are a class of statistical models used to describe the relationship between the response and covariates, based on clustered data." (1982) I chose this method because the office wanted to find out the relationship between the number of advertisements and the change in approval rating of Governor Walz.

Furthermore, Generalized Estimating Equations (GEE) were used to investigate the change in correlation between repeated measurements. According to Ma, "The GEE method focuses on average changes in response over time and the impact of covariates on these changes." (2012). In general, GEE is similar to a Generalized linear mixed model (GLMM). The biggest difference between the two methods is that the purpose of the result is different. GEE focuses on population averages and GLMM focuses on subject specific measurements. Since this study wants to know the amount of online advertisements affects changes in Walz approval ratings for the entire electorate, I used GEE.

Methods and Materials

Table 1: Summary of data.

Approval Ratings	Sex of Participants	Annual Income	The Number of Impressions	Age
Average : 60.94	Female : 32	Average : 73.74	Average : 5.087	Average : 42.48
Min : 22	Male : 18	Min : 24	Min : 1	Min : 20.94
Max : 100		Max :136	Max : 9	Max : 67.86

The data came from the results of a survey of how Minnesotan political sentiments changed during 2019. The number of participants was 50. The number of approval ratings for 50 participants was 600 because the record was recorded once a month during a year (n=600).

Participant responses were recorded under anonymous IDs. Participants gave a number indicating their support on a 0 to 100 scale, with 100 meaning an intention to support and 0 meaning no support. The average approval ratings was 60.94. The minimum was 22 and the maximum was 100. The approval ratings was recorded on the last day of the month. Participants were classified based on 4 characteristics; sex of participants, annual income (thousand dollars), age and the number of Impressions. Since I want to know the correlation between the number of impressions and approval ratings, I would more focus on the number of impressions. The number of impressions means how many online advertisements participants have encountered in a month. The average the number of impressions was 5.1 times in a month. The minimum was 1 and the maximum was 9.

I built a mixed effect model using repeated measures. According to Speelman (2018), "When data consist of grouped observations, and there is a risk that measurements within the same group are not independent, group-specific random effects can be added to a regression model in order to account for such within-group associations." Participants (ID) were randomly selected and studies were conducted to see if sex, annual income, the number of impressions and age affected the participants' changes in approval ratings. Sex, annual income, the number of impressions and age can be changed during the study, but participants' IDs cannot be changed. Therefore, ID was designated as a random effect, and sex, annual income, impressions, and age were designated as fixed effects. The mixed effect model is as follows.

$$Approval\ rating_{ij} = \beta_0 + \beta_1 Sex_j + \beta_2 Annual.income + \beta_3 Impressions + \beta_4 Age + b_i + \epsilon_{ij}$$

The approval rating is the response variable. β_0 is the constant intercept. $\beta_1 Sex_j$ is the rate of change in the response when gender is female. If participant is female, $Sex_j = 1$. If participant is male, $Sex_j = 0$. $\beta_2 Annual.income$ is the rate change in the response due to 1 unit change in annual income. $\beta_3 Impressions$ is the rate change in the response due to 1 unit change in the number of cases exposed to online advertisements over a month. $\beta_4 Age$ is the rate change in the response due to 1 unit change in age. $b_i \sim N(0, \sigma_b^2)$ is the random intercept to account for subject to subject variability. $\epsilon_{ij} \sim N(0,\sigma_b^2)$ is random within subject error. The random intercept shows that participants' approval ratings are different from the population average. If participants' approval ratings change over time, a random slope will be added to the model. The random slope indicates participants' changing approval ratings over time.

After forming multiple models, the most appropriate model was derived by the stepwise selection process with the lowest AIC. I specified the correlation structure for the selected model. This could help me determine the distribution of data in studies with small data sample sizes. According to Ma, "In addition, to account for variation in correlation between repeated measures, generalized estimating equations (GEE) allows specification of the correlation structure from a wide variety of choices [...]. This feature can greatly benefit studies in which data are skewed or the distribution of data is difficult to verify because of a small sample size." (2012) I used compound symmetry, autoregressive, and unstructured correlation structure in order to investigate the change in correlation between repeated measurements. The final model was determined after checking normality assumptions of random intercept and random slope and constant variance assumptions. Through the final model, I was able to know which effects impact the approval ratings and how the approval ratings change over time.

Results

Table 2: Description of the five models used for this analysis.

Model 1	Random intercept without interactions
Model 2	Random intercept with interactions
Model 3	Correlated random intercept and random slope without interactions
Model 4	Correlated random intercept and random slope with interactions
Model 5	Uncorrelated random intercept and random slope without interactions

I started with a model with fixed effects (Sex of Participants, Annual Income, The Number of Impressions and Age) and all two-way interactions between fixed effects. A total of five models were formed. The first model was a random intercept without interactions. The second model was a random intercept with interactions. Third model was a random intercept and a random slope correlated model without interactions. Fourth model was a random intercept and a random slope correlated model with interactions. Fifth model was a random intercept and a random slope uncorrelated model without interactions. Through a comparative analysis of the five models, I found out whether a random slope and a random intercept are correlated and there are interactions between fixed effects.

Table 3: Model comparison between model 1 and model 3.

	AIC	BIC	Chi-square	p-value
Model 1	4139.3	4200.9		
Model 3	4137.2	4207.6	6.1208	0.04687

First, checking the correlation of a random intercept and a slope, I compared the first model with the third model. The comparison between the two models shows that the third model was statistically significant from the first model (p-value : 0.04687). It means that the third model was determined to be different from the first model.

Table 4: Model comparison between model 2 and model 4.

	AIC	BIC	Chi-square	p-value
Model 2	4187.7	4513.1		
Model 4	4185.4	4519.5	6.3338	0.04213

Second, I compared the second model with the fourth model. The comparison between the two models shows that the fourth model was statistically significant from the second model (p-value : 0.04213). It means that the fourth model was determined to be different from the second model.

Table 5: Model comparison between model 3 and model 4.

	AIC	BIC	Chi-square	p-value
Model 3	4137.2	4207.6		
Model 4	4185.4	4519.5	71.848	0.1406

Third, I compared the third model and the fourth model whether there are interactions or not. The comparison between the two models shows that the fourth model was not statistically significant from the third model (p-value : 0.1406). It means that the fourth model was determined to be not different from the third model.

Table 6: Model comparison between model 3 and model 4.

	AIC	BIC	Chi-square	p-value
Model 5	4139.8	4205.7		
Model 3	4137.2	4207.6	4.5516	0.03289

Finally, I compared the third model and fifth model. The comparison between the two models shows that the third model was statistically significant from the fifth model (p-value : 0.03289). It means that the third model was determined to be different from the fifth model. Therefore, I chose the model with correlated a random intercept and a random slope on parsimony.

The third model was tested with three different covariance structures (compound symmetry, autoregressive, and unstructured) in order to investigate the change in correlation between repeated measurements through the stepwise process. By the result of the stepwise selection process, I selected the third model with autoregressive with the lowest AIC (which is 4129.508). Therefore, the final model I chose was correlated random intercept and random slope with autoregressive covariance structure. The final model is as follows.

$$\begin{aligned} Approval\ rating_{\mathrm{ij}} = {} & (\beta_0 + b_{i1}) + \beta_1 * Sex_j + \beta_2 Annual.income + \beta_3 Impressions \\ & + (\beta_4 + b_{i2}) * \mathrm{Age} + \epsilon_{ij} \end{aligned}$$

$b_{i1} \sim N(0, \sigma_{b1}^2)$ is the random intercept to account for subject to subject variability and $b_{i2} \sim N(0, \sigma_{b2}^2)$ is the random slope that indicates of each participants' changing approval ratings over time. The results from the final model are shown in Table 7 below.

Table 7: Summary of correlated random intercept and random slopes with autoregressive covariance structure model.

	Value	p-value
Intercept	60.02033	0
Sex Female	3.99096	0.1227
Age	0.04331	0.7561
Annual Income	-0.03838	0.3946
The number of impressions	-0.22761	0.038

From the result analysis, the p-values of sex, annual income, age were found to be larger than 0.05. This means that they were not statistically significant. Therefore, sex, annual income, age did not affect the change in approval rating of Governor Walz.

The point to concentrate on in the final model is the p-value of the number of impressions. Since the p-value from the number of impressions was smaller than 0.05, it was statistically significant. To be more specific, when more voters exposed themselves to online advertisements, the approval rating of Governor Walz dropped by -0.22761. In other words, the number of advertisements had a negative effect on changing approval ratings.

Discussion and Summary

The study was conducted to inform Governor Tim Walz's campaign whether the number of online advertisements affects approval ratings or not. From the result, I found that only the number of impressions affected Governor Walz's approval ratings. To be more specific, if voters were exposed to a lot of advertisements, they were more likely to respond negatively to the approval ratings. Since the p-value of age was large enough (close to 1), age was not likely to affect the Walz's approval rating. Therefore, the approval ratings were not affected by the previous month's approval ratings.

Figure1 : Constant variance assumption of correlated random intercept and random slopes with autoregressive covariance structure model.

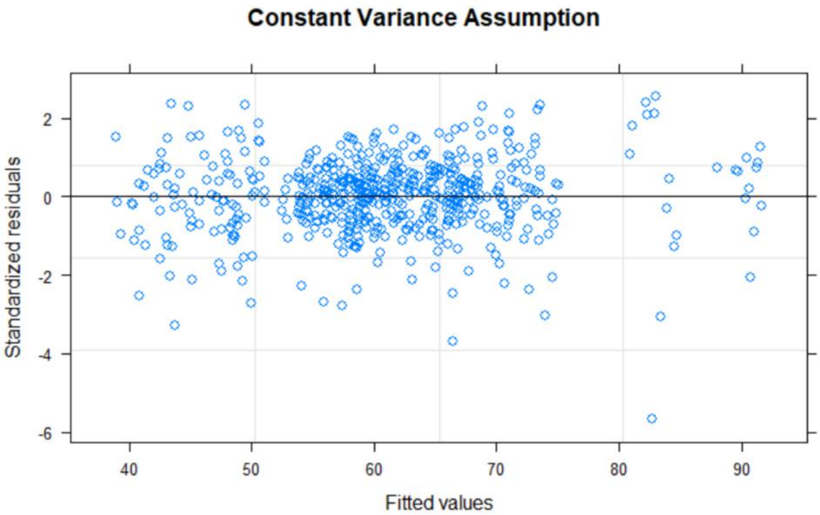
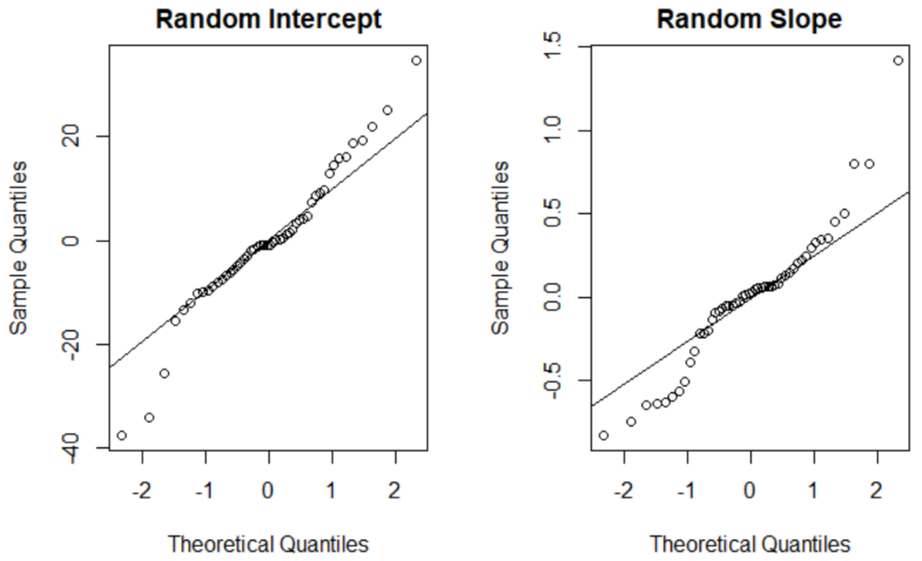


Figure 2: Normality assumptions of correlated random intercept and random slope with autoregressive covariance structure model.



Through repeated measures, I found that the amount of online advertisements negatively affects the approval ratings. Since I have confirmed that the amount of monthly changes in advertisements affects the approval ratings, the repeated measures seem to have been effective. Furthermore, figure 1 and figure 2 show that the constant variance and normality assumptions of the random intercept and random slope are fulfilled.

The limitation of the study is that only 50 voters in Minnesota were included in the data. As such, the findings of this report are not representative of the change in approval ratings of all voters in Minnesota. Also, the study did not examine whether the location of online advertisements had an effect on voters' approval ratings. This possible effect needs to be considered in future studies.

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