## Modeling Different Sources of Variability in Human Factors Experiments, TRB WORKSHOP 2020

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## **PART IV – Generalized Estimating Equations**

We will now analyze a second dependent variable, the number of glances made towards an anticipatory cue between when the cue is present and when the event happens. Since this variable is a count variable, we will use a Poisson model. In addition, we will need to offset the number of glances by the window of time an individual had to make glances. Generalized estimating equations allow for correlation without explicitly defining a model for the origin of the dependency. The following model can be fit with the **gee(**) function.

## > G.model.CS<- gee(glance\_count ~ Experience + SecondaryTask + offset(log(Time)), data = data, family = ''poisson'', corstr = ''exchangeable'', id = Participant\_ID) > summary(model)

The corstr() argument allows us to model different types of variance-covariances structures. The exchangeable structure was specified the current model, however, other options include "unstructured" or "AR-M" to allow the variance to be freely estimated or modeled as a first-order auto regressive structure respectively.

```
GEE: GENERALIZED LINEAR MODELS FOR DEPENDENT DATA
 gee S-function, version 4.13 modified 98/01/27 (1998)
Model:
 Link:
                           Logarithm
 Variance to Mean Relation: Poisson
Correlation Structure: Exchangeable
Call·
gee(formula = glance count ~ Experience + SecondaryTask + offset(log(Time)),
   id = Participant_ID, data = data, family = "poisson", corstr = "exchangeable")
Summary of Residuals:
      Min
               10
                         Median
                                        30
                                                   Max
-0.3106073 1.6033515 3.6033515 5.7840250 13.6033515
Coefficients:
                  Estimate Naive S.E.
                                        Naive z Robust S.E.
                                                               Robust z
Estimate Naive S.E. Naive z Robust S.E. Robust z
(Intercept) -0.9247049 0.06457430 -14.320013 0.05794338 -15.958767
ExperienceNovice -0.3633665 0.08475706 -4.287153 0.09008692 -4.033510
SecondaryTaskY -0.2445210 0.08469514 -2.887073 0.08290460 -2.949427
Estimated Scale Parameter: 2.129484
Number of Iterations: 2
Working Correlation
          [,1]
                     [,2] [,3]
                                         [,4]
[1,] 1.0000000 -0.1892192 -0.1892192 -0.1892192
[2,] -0.1892192 1.0000000 -0.1892192 -0.1892192
[3,] -0.1892192 -0.1892192 1.0000000 -0.1892192
[4,] -0.1892192 -0.1892192 -0.1892192 1.0000000
```

**Figure 5**: Generalized estimating model. Correlations between the different driving scenarios are shown under working correlations. Robust z values can be used to determine significance of the co-efficient estimates.