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In TV shows, there are countless methods to manipulate how much the audience trusts certain characters. Whether it's simply the narrative and genre of the story involved, or outside influences like representation and political commentary, it is difficult to objectively assess everyone involved. But even when the works are pure fiction, subtle influences like these always creep their way into analyses of humans and what to expect from each of them down the line. That is why this group decided to analyze the paper, *Facial Trustworthiness Predicts Extreme Criminal-Sentencing Outcomes* by John Paul Wilson and Nicholas O. Rule.

In this paper, two studies are conducted regarding how perception of trustworthiness affects willingness to apply punishments such as the death penalty. The first was conducted on inmates that were incarcerated in Florida during October, 2014; the second study was conducted on people convicted of murder, but exonerated afterwards, usually through DNA analysis. The data was collected through a survey available to separate groups of Americans meeting the selection criteria on Amazon Mechanical Turk. A group of 208 participants scored random sets of faces based on how trustworthy they appear on a scale of one to eight. A separate group of 141 participants scored the same sets of faces on Afrocentricity and facial maturity. Objective attributes, such as whether the subject is wearing glasses or has facial tattoos, were scored by research assistants. Analysis on the groups of raters showed that there was an acceptable level of interrater reliability, meaning that there was some level of consensus among those evaluating the images.

John Paul Wilson and Nicholas O. Rule modeled the data they collected using a logistic regression with categorical outcomes of life in prison or the death penalty. Two models were created using the color-blind data, one that only includes perceptions of trustworthiness, while the other expands to include Afrocentricity, attractiveness, facial maturity, the presence of glasses and time served. Using the two studies, the authors proved facial trustworthiness, which has questionable validity about criminal behavior, does disportionately affect criminal sentencing (Wilson, and Rule, pg. 1329). We will attempt to recreate both logistical regression models created in study two as seen below in Table 2.

Table 1: The Results of Logistic Regression in the Paper

Predictor	b	Odds ratio
Model 1		
Trustworthiness	-1.55^{*} (0.68)	0.56 [0.06, 0.80]
Intercept	5.96 (2.71)	387.72
Model 2		
Trustworthiness	$-1.47^{\dagger}$ (0.78)	0.23 [0.05, 1.06]
Afrocentricity	−0.51 (0.41)	0.60 [0.27, 1.34]
Attractiveness	−0.30 (0.86)	0.74 [0.14, 3.98]
Facial maturity	0.16 (0.53)	1.18 [0.41, 3.32]
Presence of glasses	1.14 (1.01)	3.11 [0.43, 22.66]
Time served	−0.14 (0.08)	0.87 [0.75, 1.01]
Intercept	7.49 (4.58)	1,780.52

Note: Standard errors are given in parentheses; 95% confidence intervals are given in brackets. The fit of Model 1 was good, $\chi^2(1) = 6.47$, $p = .01$, but adding the covariates in Model 2 did not improve its fit, $\Delta\chi^2(5) = 6.04$, $p = .30$, and the full model was only marginally significant, $\chi^2(6) = 12.51$, $p = .051$.
$^{\dagger}p = .06$. $^{*}p < .05$.

As shown above in Table 1, with 0 counting as life sentence and 1 serving as death penalty, logistic regression revealed that adding the covariates left little effect on the significance of trustworthiness in the sentencing. The results of the group's attempt to replicate are below in Table 2, with the code used for replication in the Appendix. Both models were fit using R's `glm()` function with the `family = "binomial"` option. The odds ratio is defined as e^b. The confidence interval is calculated using *b* first, then converting it to an odds ratio as defined before. The rest of the columns are output of the `summary()` function in R. The listed odds ratio for Model 1 is inconsistent between the tables. The paper confirms our thoughts that their table included an error. They state, "Trustworthiness significantly predicted sentencing outcomes, b = −1.55, SE = 0.68, p = .02, odds ratio = 0.21" (Wilson & Rule, 2015).

Table 2: Results of Logistic Regression for Models 1 and 2

	Predictor	b	Pr(>|z|)	Std. Error	Odds Ratio	OR 95% CI
Model 1	Intercept	5.96	0.028	2.71	387.72	NA
	Trustworthiness	-1.55	0.022	0.68	0.21	[0.06, 0.8]
Model 2	Intercept	7.48	0.101	4.57	1780.52	NA
	Trustworthiness	-1.47	0.060	0.78	0.23	[0.05, 1.06]
	Afrocentricity	-0.51	0.213	0.41	0.60	[0.27, 1.34]
	Attractiveness	-0.30	0.725	0.86	0.74	[0.14, 3.98]
	Facial maturity	0.16	0.761	0.53	1.18	[0.42, 3.32]
	Presence of glasses	1.14	0.262	1.01	3.11	[0.43, 22.66]
	Time served	-0.14	0.067	0.08	0.87	[0.75, 1.01]

We believe that the researchers chose the right model to fit. The response variable is binary, so a logistic regression model is the obvious choice. The group was able to replicate the results near exactly, with only a few rounding differences. The model that the researchers created makes sense, but does raise some additional questions. Although the research study claims that the only predictor is “trustworthiness”, it tries to explore how other variables may interact with trustworthiness to affect the outcome. They conclude that the better model is the model without additional predictor variables, which seems to leave the results of the study in a hazy area as the idea of “trustworthiness” or why consensus for this intrinsic value exists isn’t fully explored. Clearly bias and errors exist in the justice process, as seen by the exonerations in this data set. However, the study isn’t able to find what bias interacts with trustworthiness to cause these flawed outcomes.

Works Cited

Dobson, A. J., & Barnett, A. G. (2018). *An introduction to generalized linear models* (4th ed.). Boca Raton, FL: CRC Press.

R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Wilson, John Paul, and Nicholas O. Rule. "Facial Trustworthiness PredictsExtreme Criminal-Sentencing Outcomes." *Sage Journals*. Association for Psychological Science, 10 July 2015. Web. 15 Mar. 2021. <https://journals-sagepub-com.proxy.lib.ohio-state.edu/doi/full/10.1177/0956797615590992>.

Appendix A: The Group's Code and Results

model.R

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```
library(readxl)
library(tidyverse)
library(gridExtra)

## recreating the table for study 2
study2 <- read_excel("Study2 Data Unrounded.xlsx")

study2.mod1 <- glm(sent ~ trust, data = study2, family = "binomial")
summary(study2.mod1)

##
## Call:
## glm(formula = sent ~ trust, family = "binomial", data = study2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.2244  -0.8936  -0.6561   0.9816   1.6519
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   5.9603     2.7071   2.202   0.0277 *
## trust        -1.5489     0.6777  -2.286   0.0223 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 51.049  on 36  degrees of freedom
## Residual deviance: 44.581  on 35  degrees of freedom
## AIC: 48.581
##
## Number of Fisher Scoring iterations: 4

study2.mod2 <- glm(
  sent ~ trust + zAfro + attract + maturity + glasses + served,
  data = study2,
  family = "binomial"
)
summary(study2.mod2)

##
## Call:
## glm(formula = sent ~ trust + zAfro + attract + maturity + glasses +
##     served, family = "binomial", data = study2)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0923  -0.7762  -0.3484   0.8499   1.8058
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  7.48466    4.56650   1.639   0.1012
## trust       -1.47338    0.78307  -1.882   0.0599 .
## zAfro       -0.51346    0.41222  -1.246   0.2129
## attract     -0.30169    0.85817  -0.352   0.7252
## maturity     0.16135    0.53009   0.304   0.7608
## glasses      1.13605    1.01248   1.122   0.2618
## served      -0.14218    0.07765  -1.831   0.0671 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 51.049  on 36  degrees of freedom
## Residual deviance: 38.538  on 30  degrees of freedom
## AIC: 52.538
##
## Number of Fisher Scoring iterations: 4

# model coefficients
coef1 <-
  rownames_to_column(as.data.frame(summary(study2.mod1)$coefficients), var =
"Variable")
coef2 <-
  rownames_to_column(as.data.frame(summary(study2.mod2)$coefficients), var =
"Variable")

# name substitutes
names <-  data.frame(
  Variable = c(
    "(Intercept)",
    "trust",
    "zAfro",
    "attract",
    "maturity",
    "glasses",
    "served"
  ),
  Predictor = c(
    "Intercept",
    "Trustworthiness",
    "Afrocentricity",
    "Attractiveness",
    "Facial maturity",
    "Presence of glasses",
    "Time served"
  )
)

# creating odds ratio, CI, and rounding
```

```r
table <-
  bind_rows(coef1, coef2) %>%
  mutate(
    `Odds Ratio` = round(exp(Estimate), 2),
    b = round(Estimate, 2),
    or.lower = exp(Estimate - 1.96 * `Std. Error`),
    or.upper = exp(Estimate + 1.96 * `Std. Error`),
    `OR 95% CI` = paste("[", round(or.lower, 2), ", ", round(or.upper, 2), "]", sep =
""),
    `Std. Error` = round(`Std. Error`, 2),
    `Pr(>|z|)` = round(`Pr(>|z|)`, 3)
  ) %>%
  left_join(names) %>%
  select(Predictor, b, `Pr(>|z|)`, `Std. Error`, `Odds Ratio`, `OR 95% CI`)

## Joining, by = "Variable"

table

##              Predictor     b Pr(>|z|) Std. Error Odds Ratio            OR 95% CI
## 1            Intercept  5.96    0.028       2.71     387.72    [1.92, 78130.41]
## 2      Trustworthiness -1.55    0.022       0.68       0.21          [0.06, 0.8]
## 3            Intercept  7.48    0.101       4.57    1780.52 [0.23, 13728740.19]
## 4      Trustworthiness -1.47    0.060       0.78       0.23         [0.05, 1.06]
## 5       Afrocentricity -0.51    0.213       0.41       0.60         [0.27, 1.34]
## 6       Attractiveness -0.30    0.725       0.86       0.74         [0.14, 3.98]
## 7      Facial maturity  0.16    0.761       0.53       1.18         [0.42, 3.32]
## 8  Presence of glasses  1.14    0.262       1.01       3.11        [0.43, 22.66]
## 9          Time served -0.14    0.067       0.08       0.87         [0.75, 1.01]

# row names for output
rownames <- rep("", nrow(table))
rownames[table$Predictor == "Intercept"] <- c("Model 1", "Model 2")

# remove CI for both intercepts
table$`OR 95% CI`[table$Predictor == "Intercept"] <- NA

# save table
png("table2.png", height = 250, width = 500)
grid.table(table, rows = rownames)
dev.off()

## png
##   2
```