Criminology Annual Survey: Student Perceptions of Law Enforcement & Victimization: Regression Models and Statistical Analysis

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Question 1

Exploring potential correlation between Appendix F: Just-World and Sexism Scales to Appendix D: Attitudes toward Police Legitimacy Scale (APLS)

Recall:

- Appendix D: Attitudes toward Police (APLS) has 34 questions in which survey takers choose a response from 1 to 6.
- Appendix F can be broken down into 5 sections (each a survey question):
  - Global Belief in a Just World Scale (GBJW 1-7)
  - Hostile Sexism Towards Women (ASI 1-6)
  - Benevolent Sexism Towards Women (ASI 7-12)
  - Hostile Sexism Towards Men (AMI 1-6)
  - Benevolent Sexism Towards Men (AMI 7-12)

Do any of these factors from Appendix F have correlation with attitudes towards police (APLS)?

Question 1

Which section of Appendix F has the greatest correlation on attitudes towards police APLS?

Create simple linear regression models using the mean values for each section of Appendix F so that a general idea of the correlations can be found

Using the Variable Codebook

	Titles of mean columns for each predictor (We will use these for the upcoming models)
Attitude Towards Police (APLS columns 1-34)	APLS
Global Belief in a Just World Scale (GBJW columns 1-7)	GBJW
Hostile Sexism Towards Women (ASI columns 1-6)	ASI_HostileSexism
Benevolent Sexism Towards Women (ASI columns 7-12)	ASI_BenevolentSexism
Hostile Sexism Towards Men (AMI columns 1-6)	ATM_HostileSexism
Benevolent Sexism Towards Men (AMI columns 7-12)	ATM_Benevolent Sexism

Model 1 Attitude Towards Police (APLS) as response (Y) and World Views (GBJW) as predictor (X)

```
> model1 <- glm(APLS ~ GBJW, data = projectdata)
> summary(model1)

Call:
glm(formula = APLS ~ GBJW, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.72909  -0.56107   0.03341   0.51822   1.97109

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.31862    0.28225   8.215 2.37e-13 ***
GBJW         0.54237    0.08712   6.226 6.79e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.7145611)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  88.606  on 124  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 319.21

Number of Fisher Scoring iterations: 2
```

Generalized linear model comparing worldviews (GBJW) as predictor to attitudes towards police (APLS) as response.
Regression coefficient: 0.54
P-value: 6.79e-09 (significant)

There appears to be a positive correlation between world view and attitude towards police.
For each 1 unit increase in worldview, there is a 0.54 increase in attitude towards police.

Recall: attitude towards police is measured on a 1-6 scale with 6 being positive attitude

Model 2

Attitude Towards Police (APLS) as response (Y) and Hostile Sexism Towards Women (ASI_HostileSexism) as predictor (X)

```
> model2 <- glm(APLS ~ASI_HostileSexism, data = projectdata)
> summary(model2)

Call:
glm(formula = APLS ~ ASI_HostileSexism, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.52788  -0.62324   0.05664   0.63106   1.88864

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        3.42330    0.23799  14.384  < 2e-16 ***
ASI_HostileSexism  0.21747    0.08224   2.644  0.00925 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.8878533)

    Null deviance: 116.30  on 125  degrees of freedom
Residual deviance: 110.09  on 124  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 346.57

Number of Fisher Scoring iterations: 2
```

Comparing hostile sexism Women (ASI_HostileSexism) to attitude towards police (APLS).

Regression coefficient: 0.22
P-value: 0.00925 (significant)

There appears to be a positive correlation between hostile sexism towards women and attitude towards police.

Model 3

Attitude Towards Police (APLS) as response (Y) and Hostile Sexism Towards Women (ASI_HostileSexism) and World Views (GBJW) as predictors (X)

```
> model3 <- glm(APLS ~ GBJW + ASI_HostileSexism, data = projectdata)
> summary(model3)

Call:
glm(formula = APLS ~ GBJW + ASI_HostileSexism, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.66547  -0.53946   0.05276   0.51306   2.07041

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        2.21219    0.30518   7.249 4.07e-11 ***
GBJW               0.51394    0.09248   5.557 1.62e-07 ***
ASI_HostileSexism  0.07209    0.07833   0.920    0.359
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.7154427)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  87.999  on 123  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 320.34

Number of Fisher Scoring iterations: 2
```

Comparing hostile sexism Women (ASI 1-6) and worldviews (GBJW) simultaneously to attitude towards police (APLS).

Regression coefficient (worldview) : 0.52
P-value(worldview) : 1.62e-07 (significant)

Regression coefficient (hostile sexism Women) : 0.072
P-value(hostile sexism Women) : 0.359 (NOT significant)

When hostile sexism (Women) and world views are taken into account simultaneously, it is found that hostile sexism towards women has no significant effect on attitudes towards police after all. Meanwhile, world view continues to remain significant.

Model 4

Attitude Towards Police (APLS) as response (Y) and all sections of appendix F as predictors (X)

```
> model4 <- glm(APLS ~ GBJW + ASI_HostileSexism + ASI_BenevolentSexism +
+                 ATM_HostileSexism + ATM_BenevolentSexism, data = projectdata)
> summary(model4)

Call:
glm(formula = APLS ~ GBJW + ASI_HostileSexism + ASI_BenevolentSexism +
    ATM_HostileSexism + ATM_BenevolentSexism, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.52484  -0.41669   0.01837   0.54914   2.16107

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)           2.71621    0.38009   7.146 7.52e-11 ***
GBJW                  0.48814    0.09962   4.900 3.03e-06 ***
ASI_HostileSexism     0.12548    0.09595   1.308   0.1934
ASI_BenevolentSexism -0.12391    0.12000  -1.033   0.3039
ATM_HostileSexism    -0.14811    0.08894  -1.665   0.0985 .
ATM_BenevolentSexism  0.12127    0.10867   1.116   0.2667
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.6986978)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  83.844  on 120  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 320.25

Number of Fisher Scoring iterations: 2
```

Comparing all sections of appendix F (World Views, Hostile Sexism toward Women, Benevolent Sexism toward Women, Hostile Sexism toward Men, and Benevolent Sexism toward Men simultaneously to attitude towards police (APLS).

Regression coefficient (worldview) : 0.49
P-value(worldview) : 3.03e-06 (significant)

Regression coefficient (hostile sexism Women) : 0.13
P-value(hostile sexism Women) : 0.19 (NOT significant)

Regression coefficient (benevolent sexism Women) : -0.12
P-value(benevolent sexism Women) : 0.3 (NOT significant)

Regression coefficient (hostile sexism Men) : -0.15
P-value(hostile sexism Men) : 0.098 (NOT significant)

Regression coefficient (benevolent sexism Men) : 0.12
P-value(benevolent sexism Men) : 0.27 (NOT significant)

Results From Models 1-4

Model	Predictors of Attitudes Towards Police (APLS)	AIC Value
Model 1	World Views (GBJW)	319.21
Model 2	Hostile Sexism Towards Women (ASI_HostileSexism)	346.57
Model 3	Hostile Sexism Towards Women (ASI_HostileSexism) and World Views (GBJW)	320.34
Model 4	All sections of appendix F (World Views, Hostile Sexism toward Women, Benevolent Sexism toward Women, Hostile Sexism toward Men, and Benevolent Sexism toward Men)	320.25

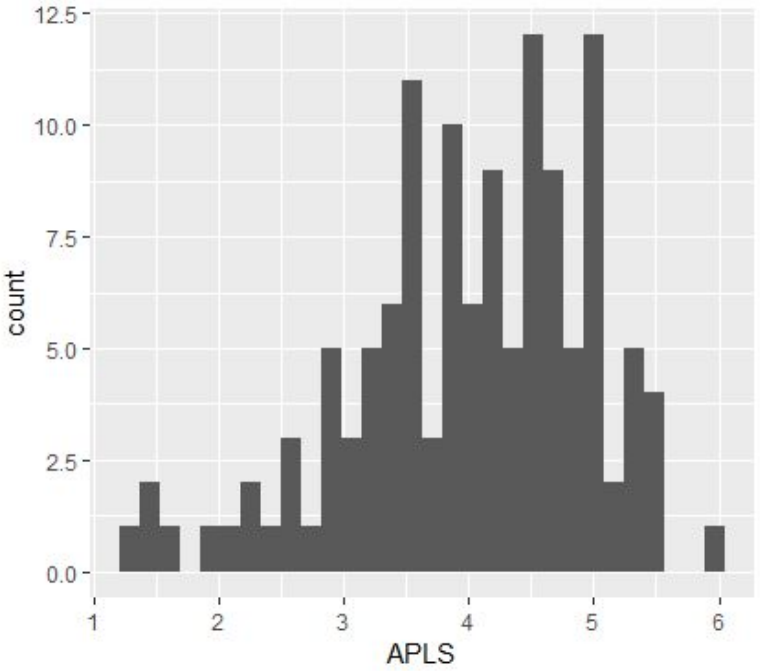
When all sections of Appendix F (World Views, Hostile Sexism toward Women, Benevolent Sexism toward Women, Hostile Sexism toward Men, and Benevolent Sexism toward Men) are taken into consideration all together, it is found that the only significant predictor of attitude toward police (Appendix D) is world views. Since Model 1 has the lowest AIC value, we consider this model to be the best fit. For each 1 unit increase in worldview, there is a 0.49 increase in attitude towards police.

Since World Views (GBJW) appears to be the only significant correlation with Attitude Towards Police (APLS), we choose Model 1 as the best response for determining which section of Appendix F has the greatest correlation on attitudes towards police APLS.

Model 1

Attitude Towards Police (APLS) as response (Y) and World Views (GBJW) as predictor (X)

```
> model1 <- glm(APLS ~ GBJW, data = projectdata)
> summary(model1)

Call:
glm(formula = APLS ~ GBJW, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.72909  -0.56107   0.03341   0.51822   1.97109

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.31862    0.28225   8.215 2.37e-13 ***
GBJW         0.54237    0.08712   6.226 6.79e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.7145611)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  88.606  on 124  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 319.21

Number of Fisher Scoring iterations: 2
```

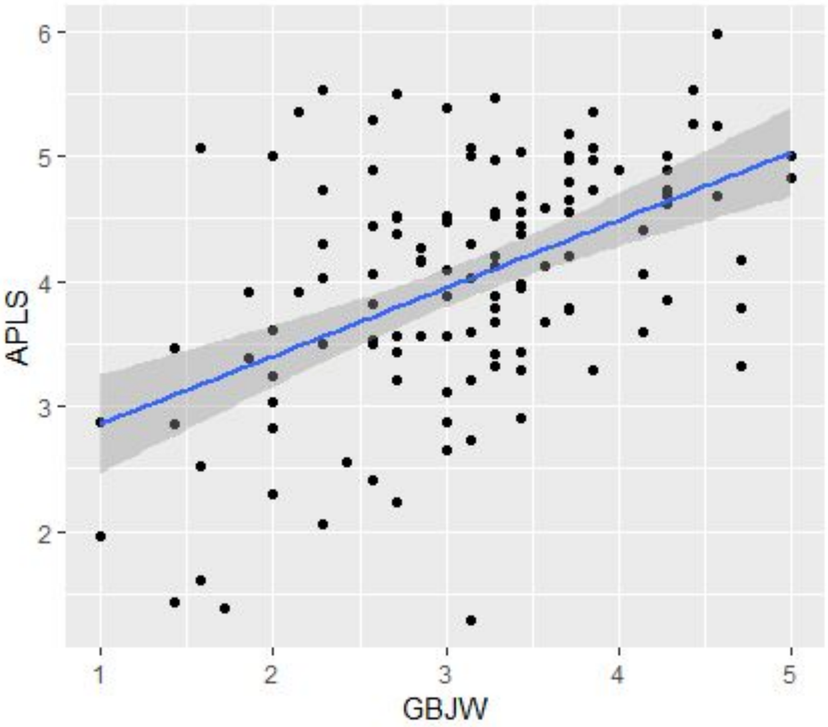


Histogram of survey responses Attitude Towards Police. On a scale of 1-6, majority of survey respondents chose between 3-5. It appears most respondents have a more positive attitude towards police.

Model 1

Attitude Towards Police (APLS) as response (Y) and World Views (GBJW) as predictor (X)

```
> model1 <- glm(APLS ~ GBJW, data = projectdata)
> summary(model1)

Call:
glm(formula = APLS ~ GBJW, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.72909  -0.56107   0.03341   0.51822   1.97109

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.31862    0.28225   8.215 2.37e-13 ***
GBJW         0.54237    0.08712   6.226 6.79e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.7145611)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  88.606  on 124  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 319.21

Number of Fisher Scoring iterations: 2
```

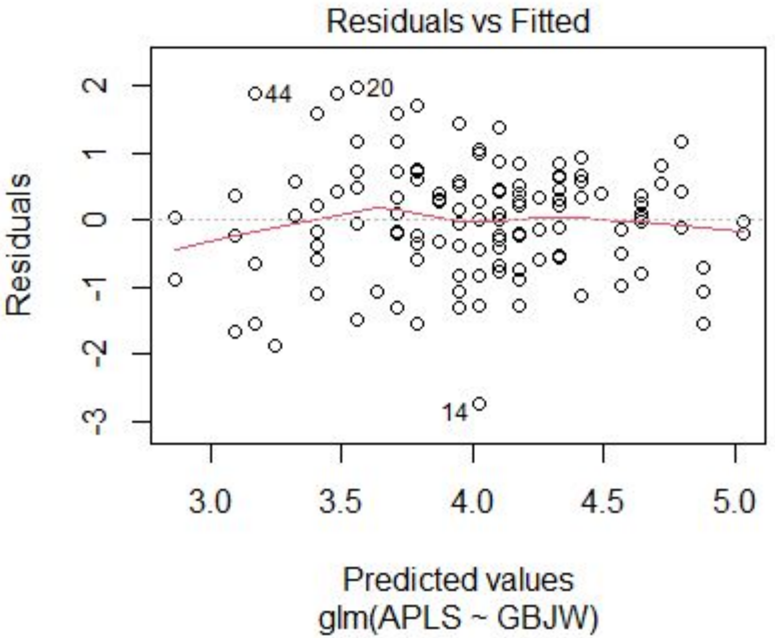


Significant relationship between GBJW and APLS

Model 1

Attitude Towards Police (APLS) as response (Y) and World Views (GBJW) as predictor (X)

```
> model1 <- glm(APLS ~ GBJW, data = projectdata)
> summary(model1)

Call:
glm(formula = APLS ~ GBJW, data = projectdata)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.72909  -0.56107   0.03341   0.51822   1.97109

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.31862    0.28225   8.215 2.37e-13 ***
GBJW         0.54237    0.08712   6.226 6.79e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.7145611)

    Null deviance: 116.302  on 125  degrees of freedom
Residual deviance:  88.606  on 124  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 319.21

Number of Fisher Scoring iterations: 2
```



Question 2

Based on survey responses to question 13 in Appendix J:

Do you intend to pursue a career related to criminal justice?

- No (0)
- Yes (1)
- I am currently employed in a criminal justice field (2)
- Prefer not to answer (9)

Using logistic regression models to explore potential correlation between interest in criminal justice careers (CJCareerInterest) as response (Y) and GBJW, APLS, ASI_HostileSexism, ASI_BenevolentSexism, ASI_HostileSexism, ATM_HostileSexism, ATM_BenevolentSexism as predictors (X)

Do any of these factors have a correlation with whether a person wants to pursue a criminal justice career (CJCareerInterest)?

- Global Belief in a Just World Scale (GBJW 1-7)
- Hostile Sexism Towards Women (ASI 1-6)
- Benevolent Sexism Towards Women (ASI 7-12)
- Hostile Sexism Towards Men (AMI 1-6)
- Benevolent Sexism Towards Men (AMI 7-12)
- Attitudes toward Police Legitimacy Scale (APLS)

Models

Model #	**Response variable ~ Predictor variable**	**Significance**
Model 5	CJCareerInterest ~ APLS	APLS not significant predictor alone
Model 6	CJCareerInterest ~ GBJW	GBJW not significant predictor alone
Model 7	CJCareerInterest ~ APLS + ATM_BenevolentSexism	APLS and ATM_BenevolentsSexism are significant predictors together
Model 8	CJCareerInterest ~ ATM_BenevolentSexism	ATM_BenevolentSexism not significant predictor alone
Model 9	CJCareerInterest ~ GBJW + APLS + ASI_HostileSexism + ASI_BenevolentSexism + ASI_HostileSexism + ATM_HostileSexism + ATM_BenevolentSexism	Only ATM_BenevolentSexism is significant when taking all potential predictors into account

Model 9

Attitude Towards Police (APLS) as response (Y) and World Views (GBJW) as predictor (X)

```
> model9 <- glm(CJCareerInterest ~
+                  GBJW + APLS + ASI_HostileSexism + ASI_BenevolentSexism + ASI_HostileSexism +
+                  ATM_HostileSexism + ATM_BenevolentSexism, data = projectdata[-59,] , family= binomial)
> summary(model9)

Call:
glm(formula = CJCareerInterest ~ GBJW + APLS + ASI_HostileSexism +
    ASI_BenevolentSexism + ASI_HostileSexism + ATM_HostileSexism +
    ATM_BenevolentSexism, family = binomial, data = projectdata[-59,
    ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.2311  -1.1894   0.6744   0.8267   1.2948

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)          -0.33964    1.20066  -0.283   0.7773
GBJW                  0.14049    0.29969   0.469   0.6392
APLS                  0.40136    0.25334   1.584   0.1131
ASI_HostileSexism     0.06583    0.26467   0.249   0.8036
ASI_BenevolentSexism  0.06127    0.33483   0.183   0.8548
ATM_HostileSexism     0.13621    0.24926   0.546   0.5848
ATM_BenevolentSexism -0.54473    0.30657  -1.777   0.0756 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 148.24  on 124  degrees of freedom
Residual deviance: 141.94  on 118  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 155.94

Number of Fisher Scoring iterations: 4
```

ATM_BenevolentSexism (benevolent sexism towards men) is significant has p-value (0.0756) when taking each potential predictor into account

Model 7

Career Interest as response (Y) and attitudes towards police (APLS) and benevolent sexism towards men (ATM_BenevolentSexism) as predictors (X)

```
> model7 <- glm(CJCareerInterest ~ APLS +
+              ATM_BenevolentSexism, data = projectdata[-59,] , family= binomial)
> #logistic regression
> summary(model7)

Call:
glm(formula = CJCareerInterest ~ APLS + ATM_BenevolentSexism,
    family = binomial, data = projectdata[-59, ])

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.1211  -1.2138   0.6975   0.8313   1.1579

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)            0.3368     0.9076   0.371   0.7106
APLS                   0.4288     0.2217   1.934   0.0531 .
ATM_BenevolentSexism  -0.3706     0.2152  -1.722   0.0850 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 148.24  on 124  degrees of freedom
Residual deviance: 142.88  on 122  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 148.88

Number of Fisher Scoring iterations: 4
```

When taking both APLS into account, ATM_BenevolentSexism has a negative relationship at the 0.1 significance level.

When taking ATM_BenevolentSexism into account, APLS has a positive relationship at the 0.1 significance level.

Possible Simpson’s paradox correlation

Factor Analysis Model 1

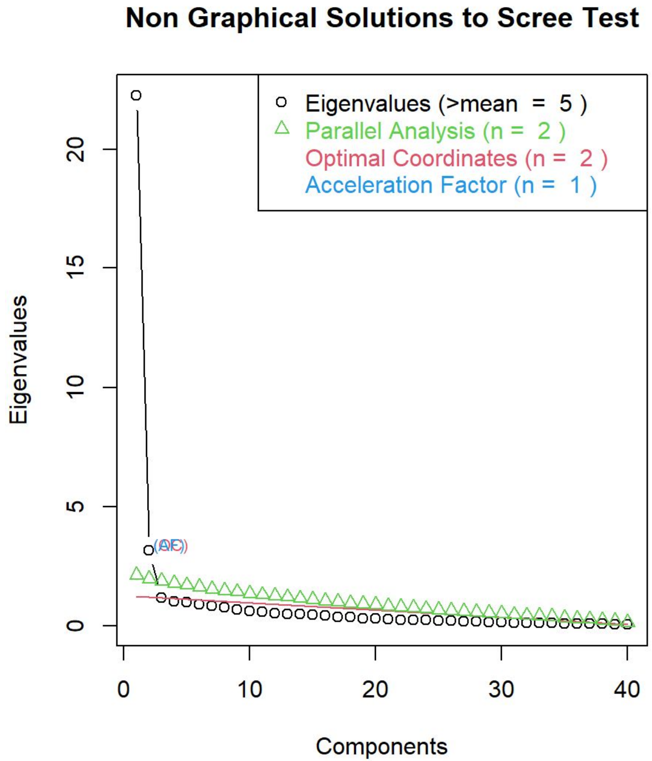
Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS)

```r
# comparing attitudes towards police 34 questions with the questions by Tyler & Jackson (2014)

apls_items <- projectdata %>% dplyr::select(APLS1:APLS34, HelpPolice_1:HelpCJS_3) %>%
  drop_na()

factanal(apls_items, 2)
```

```
               Factor1 Factor2
SS loadings     19.271   5.343
Proportion Var   0.482   0.134
Cumulative Var   0.482   0.615

Test of the hypothesis that 2 factors are sufficient.
The chi square statistic is 1142.46 on 701 degrees of freedom.
The p-value is 1.03e-23
```

Explore whether the survey questions for attitude towards police (APLS) are a part of the same factor as the questions in Helping Police (HelpPolice) and Helping Legal System (HelpCJS) derived from Tyler & Jackson (2014).

Comparing attitudes toward police questions (APLS) with the questions from Tyler & Jackson (HelpPolice & HelpCJS), we see these fit into 2 distinct factors.



Loadings:

	Factor1	Factor2
APLS1	0.861	0.150
APLS2	0.653	0.176
APLS3	0.805	0.188
APLS4	0.801	0.162
APLS5	0.826	0.274
APLS6	0.782	0.265
APLS7	0.823	0.230
APLS8	0.790	0.360
APLS9	0.518	0.519
APLS10	0.792	0.251
APLS11	0.778	0.312
APLS12	0.833	0.248
APLS13	0.778	0.249
APLS14	0.779	0.293
APLS15	0.818	
APLS16	0.736	
APLS17	0.653	0.337
APLS18	0.815	0.224
APLS19	0.740	0.181
APLS20	0.548	
APLS21	0.786	0.188
APLS22	0.761	0.252
APLS23	0.518	
APLS24	0.758	0.284
APLS25	0.546	0.238
APLS26	0.746	0.313
APLS27	0.760	0.262
APLS28	0.527	0.344
APLS29	0.763	0.276
APLS30	0.775	
APLS31	0.776	0.226
APLS32	0.826	0.234
APLS33	0.775	0.269
APLS34	0.801	0.234
HelpPolice_1	0.227	0.740
HelpPolice_2	0.267	0.680
HelpPolice_3	0.185	0.798
HelpCJS_1	0.104	0.731
HelpCJS_2	0.104	0.707
HelpCJS_3	0.149	0.727

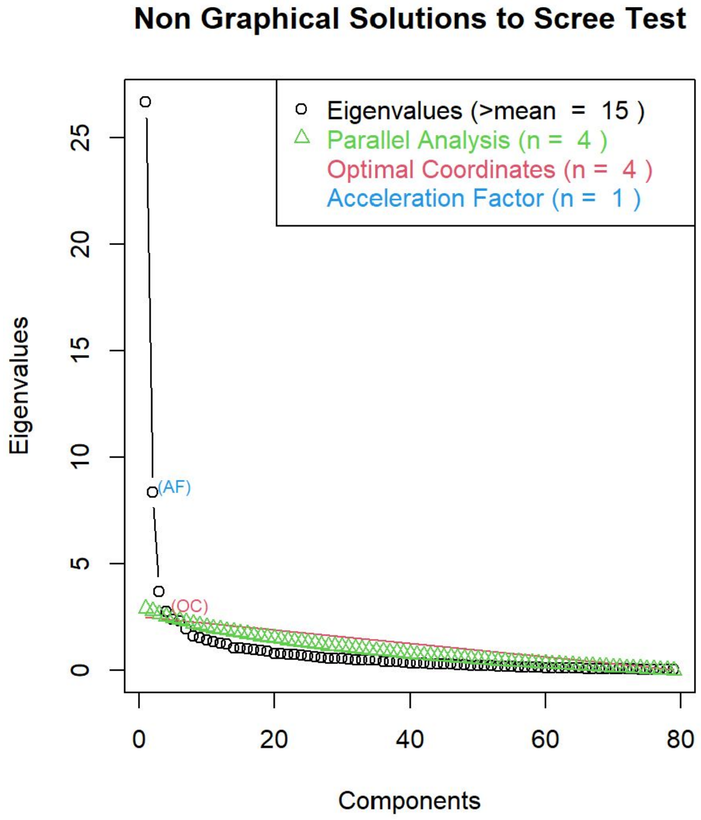
Factor Analysis Model 2 (Scree Plot)

Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS), Effectiveness of Police & Legal System [Accuracy] (Acc), Sexism Women (ASI), Sexism Men (AMI), World Views (GBJW), Effectiveness of Police & Legal System [Effectiveness] (Eff)

Appendices D,E,F

Scree plot indicates 4 factors is ideal

```
# Determine Number of Factors to Extract
ev2 <- eigen(cor(all_questions)) # get eigenvalues
ap2 <- parallel(subject=nrow(all_questions),var=ncol(all_questions),
                rep=100,cent=.05)
nS2 <- nScree(x=ev2$values, aparallel=ap2$eigen$qevpea)
plotnScree(nS2)
```



Factor Analysis Model 2

Appendices D,E,F

4 Factors

Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS), Effectiveness of Police & Legal System [Accuracy] (Acc), Sexism Women (ASI), Sexism Men (AMI), World Views (GBJW), Effectiveness of Police & Legal System [Effectiveness] (Eff)

```
# FACTOR ANALYSIS MODEL 2

all_questions <- projectdata %>% dplyr::select(APLS1:APLS34, HelpPolice_1:HelpCJS_3, Acc1:Acc4, ASI_1:ASI_12,
                                                AMI_1:AMI_12, GBJW_1:GBJW_7, Eff1:Eff4) %>% drop_na()

factanal(all_questions, 4)
```

Loadings:

	Factor1	Factor2	Factor3	Factor4
APLS1	0.868			
APLS2	0.679			
APLS3	0.810			0.125
APLS4	0.825			
APLS5	0.855		0.118	0.114
APLS6	0.811		0.135	0.116
APLS7	0.850		0.101	
APLS8	0.814		0.215	0.281
APLS9	0.611		0.390	
APLS10	0.815	0.114	0.150	
APLS11	0.806		0.186	0.124
APLS12	0.848		0.116	0.166
APLS13	0.790		0.113	0.217
APLS14	0.821		0.159	
APLS15	0.811			
APLS16	0.721	0.191		0.106
APLS17	0.708		0.216	0.143
APLS18	0.827		0.121	0.102
APLS19	0.748			0.155
APLS20	0.540	0.190		-0.107
APLS21	0.802			
APLS22	0.792	0.123	0.137	
APLS23	0.526			
APLS24	0.794		0.184	
APLS25	0.574		0.132	
APLS26	0.786	0.121	0.200	
APLS27	0.801		0.131	
APLS28	0.600	-0.130	0.221	
APLS29	0.782	0.103	0.162	
APLS30	0.771			0.185
APLS31	0.783	0.189	0.112	
APLS32	0.828	0.163	0.119	0.139
APLS33	0.792	0.228	0.151	
APLS34	0.808	0.248	0.115	
HelpPolice_1	0.351		0.724	
HelpPolice_2	0.372		0.625	
HelpPolice_3	0.302		0.767	0.115
HelpCJS_1	0.210		0.729	
HelpCJS_2	0.210		0.619	0.125
HelpCJS_3	0.256		0.646	
Acc1	0.595	0.247		0.151
Acc2	0.727	0.193	0.212	
Acc3	-0.199			-0.219
Acc4	-0.381		-0.165	
ASI_1		0.665		
ASI_2	0.160	0.562	-0.143	
ASI_3	0.103	0.686	-0.168	
ASI_4		0.531		
ASI_5	0.211	0.627		0.127
ASI_6	0.283	0.556	-0.218	
ASI_7	0.121	0.479		
ASI_8	0.170	0.471		
ASI_9	0.166	0.597		
ASI_10		0.590		
ASI_11	-0.133	0.369		0.131
ASI_12		0.682		
AMI_1	-0.163	0.427		
AMI_2		0.468	0.184	
AMI_3	-0.231	0.333	0.368	
AMI_4		0.684	0.124	
AMI_5	-0.157	0.527		
AMI_6	-0.282	0.430		
AMI_7	0.259	0.453		
AMI_8	0.113	0.476		-0.132
AMI_9	0.159	0.618		
AMI_10		0.593		-0.102
AMI_11	0.223	0.537		
AMI_12	0.241	0.463		
GBJW_1	0.342	0.345		
GBJW_2	0.369	0.174		
GBJW_3	0.371	0.226		
GBJW_4	0.143	0.472	-0.181	0.143
GBJW_5	0.215	0.323		
GBJW_6	0.588	0.261	-0.109	
GBJW_7	0.431	0.258		0.141
Eff1	0.589			0.424
Eff2	0.547	0.179		0.433
Eff3	0.296		0.172	0.865
Eff4	0.315		0.126	0.772

	Factor1	Factor2	Factor3	Factor4
SS loadings	24.217	8.283	4.046	2.397
Proportion Var	0.307	0.105	0.051	0.030
Cumulative Var	0.307	0.411	0.463	0.493

```
Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 3811.21 on 2771 degrees of freedom.
The p-value is 2.31e-36
>
```

Summary of Factor Analysis Model 2 (With 4 Factors)

- APLS is correlated with Factor 1
- Acc1 and Acc2 are correlated with Factor 1, but Acc3 and Acc4 do not appear to be correlated with any particular factor
- HelpPolice and HelpCJS are correlated with Factor 3
- ASI and AMI are correlated with Factor 2
- Most of GBJW is contained within Factor 1, but GBJW_1 and GBJW_5 are similarly correlated with both factors 1 and 2. Also, GBJW_4 is correlated with Factor 2 and not Factor 1
- Eff1 and Eff2 are correlated with Factor 1
- Eff3 and Eff4 are correlated with Factor 4.

Factors	F1	F2	F3	F4
	APLS	ASI	HelpPolice	Eff3 & Eff4
	Acc1 & Acc2	AMI	HelpCJS	
	Eff1 & Eff2			
	GBJW_1–7 (except for GBJW_4)	GBJW_1 GBJW_4 GBJW_5		

Factor Analysis Model 2

Appendices D,E,F

5 Factors

Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS), Effectiveness of Police & Legal System [Accuracy] (Acc), Sexism Women (ASI), Sexism Men (AMI), World Views (GBJW), Effectiveness of Police & Legal System [Effectiveness] (Eff)

Loadings:

	Factor1	Factor2	Factor3	Factor4	Factor5
APLS1	0.856			0.150	
APLS2	0.683				
APLS3	0.787			0.211	0.121
APLS4	0.821			0.104	
APLS5	0.829		0.117	0.224	0.112
APLS6	0.814		0.114		0.111
APLS7	0.864				
APLS8	0.813		0.200	0.116	0.275
APLS9	0.605		0.383	0.101	
APLS10	0.824	0.119	0.132		
APLS11	0.801		0.177	0.115	0.118
APLS12	0.828		0.112	0.198	0.163
APLS13	0.797				0.210
APLS14	0.815		0.143	0.132	
APLS15	0.796			0.158	
APLS16	0.682	0.148		0.288	0.105
APLS17	0.700		0.212	0.116	0.139
APLS18	0.826		0.111		
APLS19	0.727			0.180	0.151
APLS20	0.527	0.173		0.139	-0.111
APLS21	0.775			0.223	
APLS22	0.802	0.130	0.115		
APLS23	0.536				
APLS24	0.808		0.160		
APLS25	0.534		0.143	0.281	
APLS26	0.782	0.110	0.182	0.128	
APLS27	0.812		0.114		
APLS28	0.603	-0.136	0.202		
APLS29	0.796	0.112	0.139		
APLS30	0.762			0.115	0.178
APLS31	0.767	0.166	0.107	0.185	
APLS32	0.818	0.146	0.108	0.161	0.134
APLS33	0.772	0.198	0.145	0.220	
APLS34	0.795	0.226	0.104	0.183	
HelpPolice_1	0.354		0.725		
HelpPolice_2	0.378		0.617		
HelpPolice_3	0.299		0.783		0.114
HelpCJS_1	0.225		0.716		
HelpCJS_2	0.211		0.624		0.126
HelpCJS_3	0.257		0.650		
Acc1	0.591	0.239		0.120	0.148
Acc2	0.737	0.197	0.190		
Acc3	-0.183				-0.219
Acc4	-0.388		-0.157		
ASI_1		0.691			
ASI_2	0.163	0.562	-0.160		
ASI_3		0.679	-0.179	0.115	
ASI_4		0.555			-0.103
ASI_5	0.234	0.651			0.117
ASI_6	0.265	0.530	-0.224	0.182	
ASI_7	0.104	0.459		0.163	
ASI_8	0.157	0.450		0.152	
ASI_9	0.163	0.585		0.114	
ASI_10		0.546		0.246	
ASI_11	-0.129	0.373			0.129
ASI_12		0.645		0.223	
AMI_1	-0.141	0.458			
AMI_2		0.495	0.170		
AMI_3	-0.182	0.393	0.351	-0.220	
AMI_4		0.715	0.111		
AMI_5	-0.122	0.568		-0.128	
AMI_6	-0.244	0.476		-0.163	
AMI_7	0.241	0.428		0.164	
AMI_8		0.416		0.315	-0.126
AMI_9	0.139	0.589		0.187	
AMI_10	-0.101	0.556		0.221	
AMI_11	0.218	0.526		0.113	
AMI_12	0.234	0.454		0.104	
GBJW_1	0.237	0.237		0.618	
GBJW_2	0.266			0.597	
GBJW_3	0.252	0.101		0.686	
GBJW_4		0.400	-0.154	0.430	0.156
GBJW_5	0.119	0.227	0.131	0.553	
GBJW_6	0.494	0.155		0.589	
GBJW_7	0.331	0.148		0.598	0.160
Eff1	0.599				0.416
Eff2	0.539	0.167		0.126	0.428
Eff3	0.313		0.164		0.863
Eff4	0.312		0.127		0.772

Summary of Factor Analysis Model 2 (With 5 Factors)

- The observations of APLS are correlated with Factor 1
- The observations of HelpPolice and HelpCJS are correlated with Factor 3
- The observations of ASI and AMI are correlated with Factor 2
- Acc1 and Acc2 are correlated with Factor 1, but Acc3 and Acc4 are not correlated with any factors. Even when increasing factor amount to 6, 7, and 8, Acc3 and Acc4 continued to not be correlated with any factor.
- GBJW is correlated with Factor 4
- Eff1 and Eff2 are correlated with Factor 1, but Eff3 and Eff4 are correlated with Factor 5.

Factors

F1	F2	F3	F4	F5
APLS	ASI	HelpPolice	GBJW	Eff3 & Eff4
Acc1 & Acc2	AMI	HelpCJS		
Eff1 & Eff2				

Comparing Both Models (4 Factors and 5 Factors)

4 Factors

F1	F2	F3	F4
APLS	ASI	HelpPolice	Eff3 & Eff4
Acc1 & Acc2	AMI	HelpCJS	
Eff1 & Eff2			
GBJW_1–7 (except for GBJW_4)	GBJW_1 GBJW_4 GBJW_5		

5 Factors

F1	F2	F3	F4	F5
APLS	ASI	HelpPolice	GBJW	Eff3 & Eff4
Acc1 & Acc2	AMI	HelpCJS		
Eff1 & Eff2				

Similarities between Factors 4 and 5

- APLS with factor 1
- Acc1 & Acc2 with factor 1
- Eff1 & Eff2 with factor 1
- ASI & AMI with factor 2
- HelpPolice & HelpCJS with factor 3
- Eff3 & Eff4 with their own factor
- Acc3 & Acc4 belong to no factor

Differences

- GBJW was originally split between factor 1 & 2, but with the 5 factor model, it becomes correlated with its own factor 4.
- Eff3 & Eff4 with factor 5 instead of 4

Factor Analysis Model 2

Appendices D,E,F 4 Factors

(With Reverse Scoring for Acc3 & Acc4)

Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS), Effectiveness of Police & Legal System [Accuracy] (Acc), Sexism Women (ASI), Sexism Men (AMI), World Views (GBJW), Effectiveness of Police & Legal System [Effectiveness] (Eff)

Loadings:

	Factor1	Factor2	Factor3	Factor4
APLS1	0.868			
APLS2	0.679			
APLS3	0.810			0.125
APLS4	0.825			
APLS5	0.855		0.118	0.114
APLS6	0.811		0.135	0.116
APLS7	0.850		0.101	
APLS8	0.814		0.215	0.281
APLS9	0.611		0.390	
APLS10	0.815	0.114	0.150	
APLS11	0.806		0.186	0.124
APLS12	0.848		0.116	0.166
APLS13	0.790		0.113	0.217
APLS14	0.821		0.159	
APLS15	0.811			
APLS16	0.721	0.191		0.106
APLS17	0.708		0.216	0.143
APLS18	0.827		0.121	0.102
APLS19	0.748			0.155
APLS20	0.540	0.190		-0.107
APLS21	0.802			
APLS22	0.792	0.123	0.137	
APLS23	0.526			
APLS24	0.794		0.184	
APLS25	0.574		0.132	
APLS26	0.786	0.121	0.200	
APLS27	0.801		0.131	
APLS28	0.600	-0.130	0.221	
APLS29	0.782	0.103	0.162	
APLS30	0.771			0.185
APLS31	0.783	0.189	0.112	
APLS32	0.828	0.163	0.119	0.139
APLS33	0.792	0.228	0.151	
APLS34	0.808	0.248	0.115	
HelpPolice_1	0.351		0.724	
HelpPolice_2	0.372		0.625	
HelpPolice_3	0.302		0.767	0.115
HelpCJS_1	0.210		0.729	
HelpCJS_2	0.210		0.619	0.125
HelpCJS_3	0.256		0.646	
Acc1	0.595	0.247		0.151
Acc2	0.727	0.193	0.212	
Acc3	0.199			0.219
Acc4	0.381		0.165	
ASI_1		0.665		
ASI_2	0.160	0.562	-0.143	
ASI_3	0.103	0.686	-0.168	
ASI_4		0.531		
ASI_5	0.211	0.627		0.127
ASI_6	0.283	0.556	-0.218	
ASI_7	0.121	0.479		
ASI_8	0.170	0.471		
ASI_9	0.166	0.597		
ASI_10		0.590		
ASI_11	-0.133	0.369		0.131
ASI_12		0.682		
AMI_1	-0.163	0.427		
AMI_2		0.468	0.184	
AMI_3	-0.231	0.333	0.368	
AMI_4		0.684	0.124	
AMI_5	-0.157	0.527		
AMI_6	-0.282	0.430		
AMI_7	0.259	0.453		
AMI_8	0.113	0.476		-0.132
AMI_9	0.159	0.618		
AMI_10		0.593		-0.102
AMI_11	0.223	0.537		
AMI_12	0.241	0.463		
GBJW_1	0.342	0.345		
GBJW_2	0.369	0.174		
GBJW_3	0.371	0.226		
GBJW_4	0.143	0.472	-0.181	0.143
GBJW_5	0.215	0.323		
GBJW_6	0.588	0.261	-0.109	
GBJW_7	0.431	0.258		0.141
Eff1	0.589			0.424
Eff2	0.547	0.179		0.433
Eff3	0.296		0.172	0.865
Eff4	0.315		0.126	0.772

(With Reverse Scoring for Acc3 & Acc4)

Summary of Factor Analysis Model 2 (With 4 Factors)

- All of APLS is correlated with factor 1
- All of Acc is correlated with factor 1, but Acc3 is also correlated with factor 4
- GBJW 1-3 and 6-7 are correlated with factor 1, but GBJW 4 & 5 are correlated with factor 2
- Eff 1-2 is correlated with factor 1, but Eff 3-4 is correlated with factor 4
- ASI and AMI are correlated with factor 2, but AMI_3 is also correlated with factor 3
- HelpPolice and HelpCJS are correlated with factor 3

Factors

F1	F2	F3	F4
APLS	ASI	HelpPolice	Acc3
Acc	AMI	HelpCJS	Eff3 & Eff4
GBJW 1-3, and 6-7	GBJW_4 GBJW_5	AMI_3	
Eff 1-2			

Factor Analysis Model 2

Appendices D,E,F — 5 Factors

Attitudes Towards Police (APLS), Helping Police (HelpPolice), Helping Legal System (HelpCJS), Effectiveness of Police & Legal System [Accuracy] (Acc), Sexism Women (ASI), Sexism Men (AMI), World Views (GBJW), Effectiveness of Police & Legal System [Effectiveness] (Eff)

(With Reverse Scoring for Acc3 & Acc4)

	Factor1	Factor2	Factor3	Factor4	Factor5
APLS1	0.856			0.150	
APLS2	0.683				
APLS3	0.787			0.211	0.121
APLS4	0.821			0.104	
APLS5	0.829		0.117	0.224	0.112
APLS6	0.814		0.114		0.111
APLS7	0.864				
APLS8	0.813		0.200	0.116	0.275
APLS9	0.605		0.383	0.101	
APLS10	0.824	0.119	0.132		
APLS11	0.801		0.177	0.115	0.118
APLS12	0.828		0.112	0.198	0.163
APLS13	0.797				0.210
APLS14	0.815		0.143	0.132	
APLS15	0.796			0.158	
APLS16	0.682	0.148		0.288	0.105
APLS17	0.700		0.212	0.116	0.139
APLS18	0.826		0.111		
APLS19	0.727			0.180	0.151
APLS20	0.527	0.173		0.139	-0.111
APLS21	0.775			0.223	
APLS22	0.802	0.130	0.115		
APLS23	0.536				
APLS24	0.808		0.160		
APLS25	0.534		0.143	0.281	
APLS26	0.782	0.110	0.182	0.128	
APLS27	0.812		0.114		
APLS28	0.603	-0.136	0.202		
APLS29	0.796	0.112	0.139		
APLS30	0.762			0.115	0.178
APLS31	0.767	0.166	0.107	0.185	
APLS32	0.818	0.146	0.108	0.161	0.134
APLS33	0.772	0.198	0.145	0.220	
APLS34	0.795	0.226	0.104	0.183	
HelpPolice_1	0.354		0.725		
HelpPolice_2	0.378		0.617		
HelpPolice_3	0.299		0.783		0.114
HelpCJS_1	0.225		0.716		
HelpCJS_2	0.211		0.624		0.126
HelpCJS_3	0.257		0.650		
Acc1	0.591	0.239		0.120	0.148
Acc2	0.737	0.197	0.190		
Acc3	0.183				0.219
Acc4	0.388		0.157		
ASI_1		0.691			
ASI_2	0.163	0.562	-0.160		
ASI_3		0.679	-0.179	0.115	
ASI_4		0.555			-0.103
ASI_5	0.234	0.651			0.117
ASI_6	0.265	0.530	-0.224	0.182	
ASI_7	0.104	0.459		0.163	
ASI_8	0.157	0.450		0.152	
ASI_9	0.163	0.585		0.114	
ASI_10		0.546		0.246	
ASI_11	-0.129	0.373			0.129
ASI_12		0.645		0.223	
AMI_1	-0.141	0.458			
AMI_2		0.495	0.170		
AMI_3	-0.182	0.393	0.351	-0.220	
AMI_4		0.715	0.111		
AMI_5	-0.122	0.568		-0.128	
AMI_6	-0.244	0.476		-0.163	
AMI_7	0.241	0.428		0.164	
AMI_8		0.416		0.315	-0.126
AMI_9	0.139	0.589		0.187	
AMI_10	-0.101	0.556		0.221	
AMI_11	0.218	0.526		0.113	
AMI_12	0.234	0.454		0.104	
GBJW_1	0.237	0.237		0.618	
GBJW_2	0.266			0.597	
GBJW_3	0.252	0.101		0.686	
GBJW_4		0.400	-0.154	0.430	0.156
GBJW_5	0.119	0.227	0.131	0.553	
GBJW_6	0.494	0.155		0.589	
GBJW_7	0.331	0.148		0.598	0.160
Eff1	0.599				0.416
Eff2	0.539	0.167		0.126	0.428
Eff3	0.313		0.164		0.863
Eff4	0.312		0.127		0.772

(With Reverse Scoring for Acc3 & Acc4)

Summary of Factor Analysis Model 2 (With 5 Factors)

- All of APLS is correlated with factor 1
- All of Acc is correlated with factor 1, but Acc3 is also correlated with factor 5
- Eff1 & Eff2 is correlated with factor 1, while Eff3 & Eff4 is correlated with factor 5
- ASI and AMI are correlated with factor 2, but AMI_3 is also correlated with factor 3
- All of GBJW is correlated with factor 4, but GBJW_4 is also correlated with factor 2
- HelpPolice and HelpCJS are correlated with factor 3

Factors

F1	F2	F3	F4	F5
APLS	ASI	HelpPolice	GBJW	Eff3 & Eff4
Acc	AMI	HelpCJS		Acc_3
Eff1 & Eff2	GBJW_4	AMI_3		

Comparing the use of the two factor analysis functions, factanal() and fa(), to explore factor analysis model 1

Using factanal(), APLS appears to distinctly be a part of factor 1, with HelpPolice and HelpCJS part of factor 2.

factanal()

Loadings:

	Factor1	Factor2
APLS1	0.861	0.150
APLS2	0.653	0.176
APLS3	0.805	0.188
APLS4	0.801	0.162
APLS5	0.826	0.274
APLS6	0.782	0.265
APLS7	0.823	0.230
APLS8	0.790	0.360
APLS9	0.518	0.519
APLS10	0.792	0.251
APLS11	0.778	0.312
APLS12	0.833	0.248
APLS13	0.778	0.249
APLS14	0.779	0.293
APLS15	0.818	
APLS16	0.736	
APLS17	0.653	0.337
APLS18	0.815	0.224
APLS19	0.740	0.181
APLS20	0.548	
APLS21	0.786	0.188
APLS22	0.761	0.252
APLS23	0.518	
APLS24	0.758	0.284
APLS25	0.546	0.238
APLS26	0.746	0.313
APLS27	0.760	0.262
APLS28	0.527	0.344
APLS29	0.763	0.276
APLS30	0.775	
APLS31	0.776	0.226
APLS32	0.826	0.234
APLS33	0.775	0.269
APLS34	0.801	0.234
HelpPolice_1	0.227	0.740
HelpPolice_2	0.267	0.680
HelpPolice_3	0.185	0.798
HelpCJS_1	0.104	0.731
HelpCJS_2	0.104	0.707
HelpCJS_3	0.149	0.727

```
library(psych)
output <- fa(apls_items, nfactors = 2)
output$loadings # factor loadings
```

Using fa(), we also get that APLS is part of factor 1 and HelpPolice and HelpCJS factor 2.

fa()

Loadings:

	MR1	MR2
APLS1	0.917	-0.102
APLS2	0.685	
APLS3	0.844	
APLS4	0.838	
APLS5	0.843	
APLS6	0.804	
APLS7	0.858	
APLS8	0.786	0.154
APLS9	0.457	0.402
APLS10	0.821	
APLS11	0.794	
APLS12	0.855	
APLS13	0.803	
APLS14	0.794	
APLS15	0.886	-0.191
APLS16	0.801	-0.149
APLS17	0.652	0.161
APLS18	0.847	
APLS19	0.787	
APLS20	0.596	-0.115
APLS21	0.815	
APLS22	0.777	
APLS23	0.553	
APLS24	0.772	
APLS25	0.550	
APLS26	0.751	0.120
APLS27	0.788	
APLS28	0.502	0.220
APLS29	0.772	
APLS30	0.835	-0.156
APLS31	0.799	
APLS32	0.853	
APLS33	0.795	
APLS34	0.822	
HelpPolice_1		0.716
HelpPolice_2	0.151	0.645
HelpPolice_3		0.794
HelpCJS_1		0.758
HelpCJS_2		0.737
HelpCJS_3		0.749

Cronbach's Alpha Both Models (4 Factors and 5 Factors)

Factor Analysis Model 1

```
Cronbach's alpha for the 'apls_items' data-set

Items: 40
Sample units: 126
alpha: 0.978
```

Factor Analysis Model 2 (Same for both 4 and 5 factors)

```
Cronbach's alpha for the 'all_questions' data-set

Items: 79
Sample units: 125
alpha: 0.962
```

- Alpha is > 0.7 for both models, indicating reliability
- Despite factor analysis model 2 having a much larger number of items/questions than model 1, it produces a smaller value of alpha
- It appears that model 1 (APLS, HelpPolice, HelpCJS) may be a slightly more reliable model than model 2, which accounts for all questions in appendices D,E, and F.

Does Police Attitude (APLS) Correlate to Type of Criminal Justice Career Chosen (CJFutureCareer)?

Multinomial Log-Linear Model Using multinom() function from library(nnet)

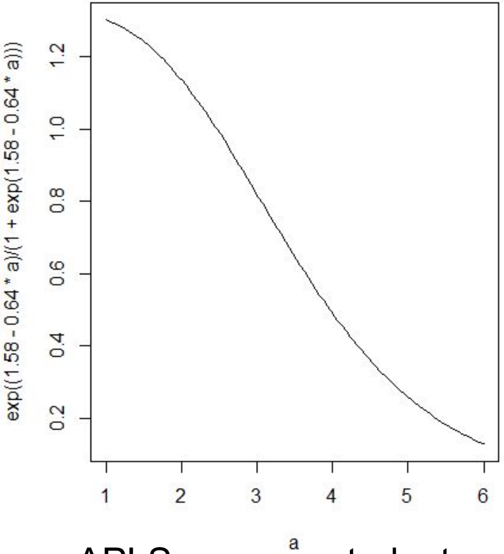
```
multi_mo <- multinom(CJFutureCareer ~ APLS, data = projectdata )
summary(multi_mo)
```

```
# CAREER 2
exp(1.58-.64*1)/(1+exp(1.58-.64*1))
# 72 percent chance they want to go to career 2 if they have a 1 response average in apls
exp(1.58-.64*6)/(1+exp(1.58-.64*6))
exp(1.58-.64*4)/(1+exp(1.58-.64*4))
a <- seq(1,6,length.out=100)
plot(a, exp((1.58-.64*a)/(1+exp(1.58-.64*a))), type ="l")
```

```
Coefficients:
   (Intercept)       APLS
2    1.57819406 -0.6423833
3   -7.50029114  1.8085158
4   -0.42527505  0.2110307
5   -0.11932788  0.3760651
6   -3.41090667  0.9988216
7    0.09208763  0.3092070
9    2.59688688 -0.3657784
10  -1.87064612  0.3946813
11  -0.07243780  0.3324459
```

```
> table(projectdata$CJFutureCareer)

 1  2  3  4  5  6  7  9 10 11 
 4  2  7  6 16  9 15 14  3 15 
```

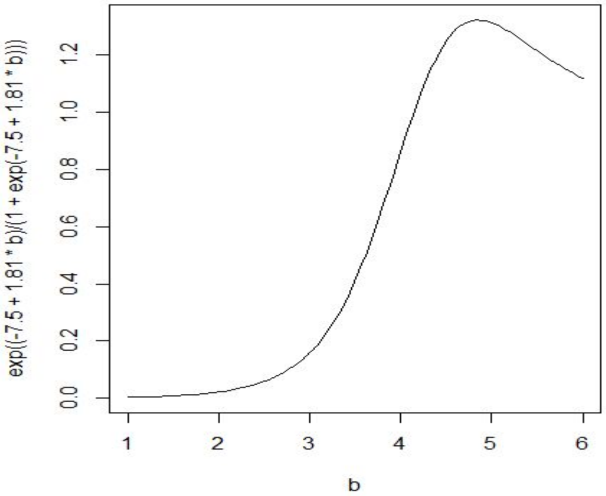
Example: If a student has an average response of 1 in APLS, there is a 72% chance they want to go into career 2

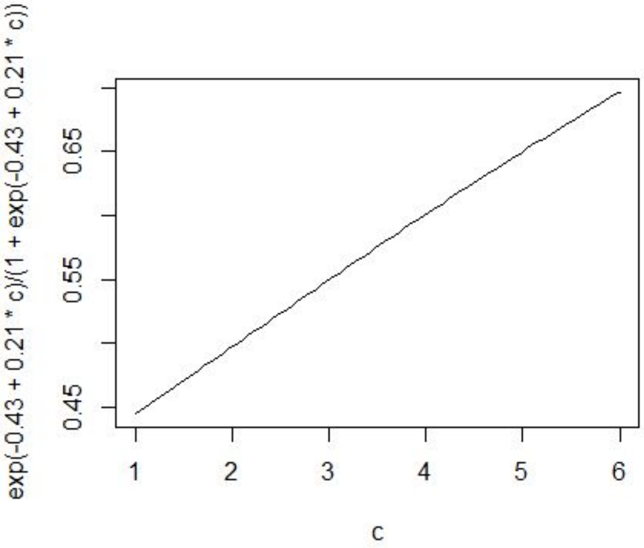


APLS average student response

CJ Careers 3 and 4

```
# CAREER 3
exp(-7.5+1.81*1)/(1+exp(-7.5+1.81*1))
# 0.34 percent chance they want to go to career 3 if they have a 1 response avg in apls
exp(-7.5+1.81*4)/(1+exp(-7.5+1.81*4))
# 43.5 percent chance they want to go to career 3 if they have a 4 response avg in apls
b <- seq(1,6,length.out=100)
plot(b, exp((-7.5+1.81*b)/(1+exp(-7.5+1.81*b))), type ="l")
```

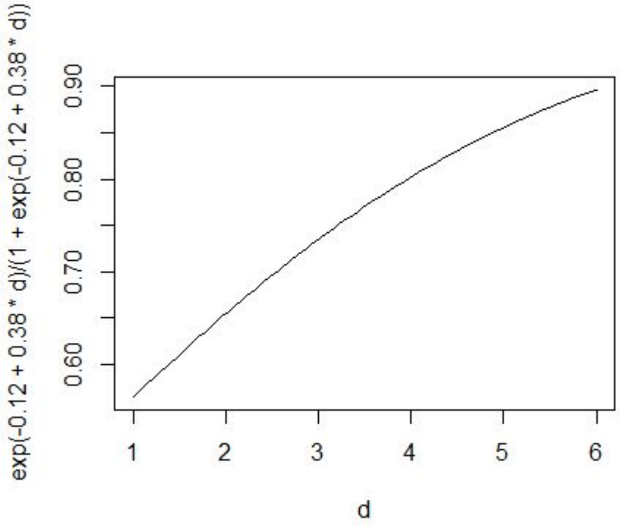


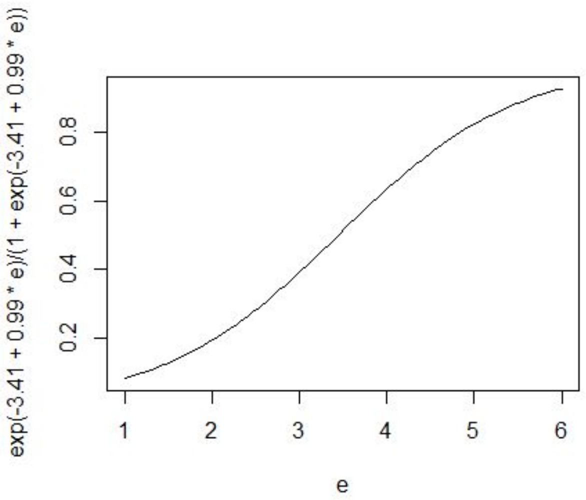



```
# CAREER 4
exp(-0.43+.21*2)/(1+exp(-0.43+.21*2))
# 50 percent chance they want to go to career 4 if they have a 2 response avg in apls
exp(-0.43+.21*5)/(1+exp(-0.43+.21*5))
c <- seq(1,6,length.out=100)
plot(c, exp(-0.43+.21*c)/(1+exp(-0.43+.21*c)), type ="l")
```

CJ Careers 5 and 6

```
# CAREER 5
exp(-.12+.38*3)/(1+exp(-0.12+.38*3))
# 73 percent chance they want to go to career 5 if they have a 3 response avg in apls
exp(-.12+.38*5)/(1+exp(-0.12+.38*5))
d <- seq(1,6,length.out=100)
plot(d, exp(-.12+.38*d)/(1+exp(-0.12+.38*d)), type ="l")
```

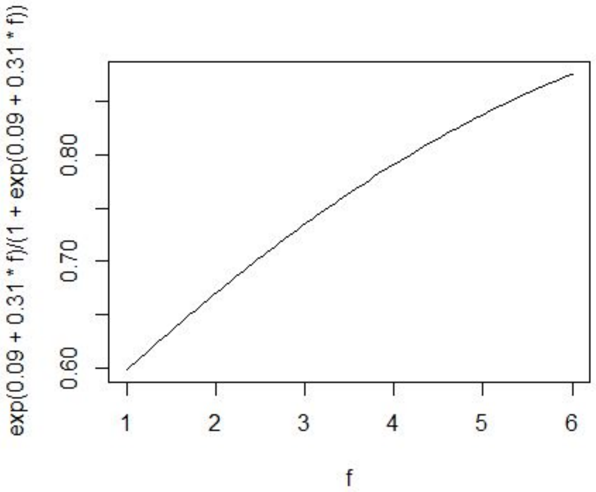


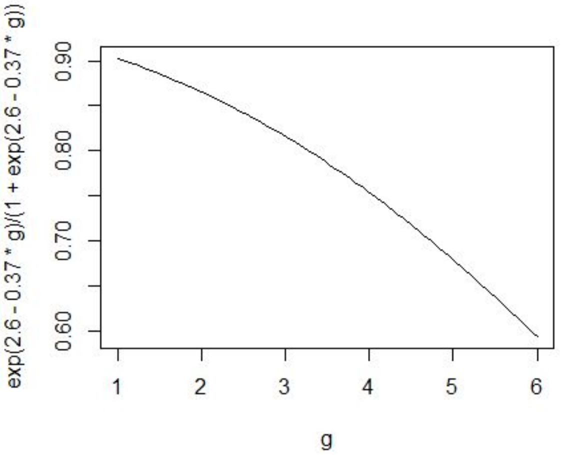



```
# CAREER 6
exp(-3.41+.99*3)/(1+exp(-3.41+.99*3))
# 39 percent chance they want to go to career 6 if they have a 3 response avg in apls
e <- seq(1,6,length.out=100)
plot(e, exp(-3.41+.99*e)/(1+exp(-3.41+.99*e)), type ="l")
```

CJ Careers 7 and 9

```
# CAREER 7
exp(.09+.31*4)/(1+exp(.09+.31*4))
# 79 percent chance they want to go to career 7 if they have a 4 response avg in apls
f <- seq(1,6,length.out=100)
plot(f, exp(.09+.31*f)/(1+exp(.09+.31*f)), type ="l")
```

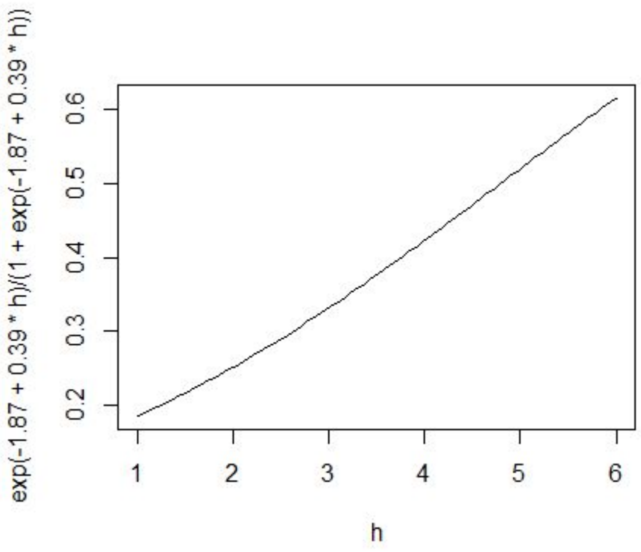


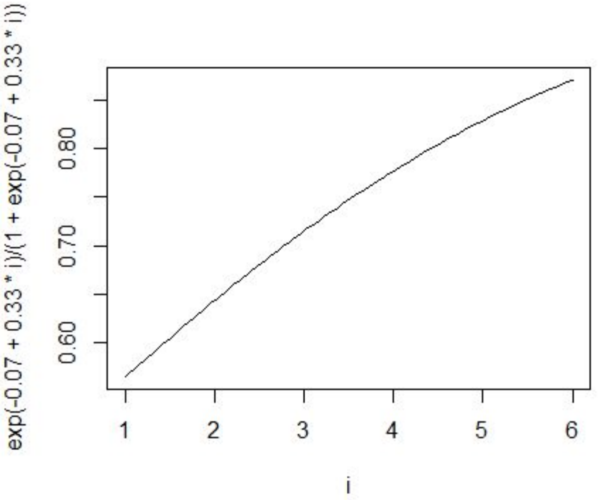



```
# CAREER 9
exp(2.6-.37*4)/(1+exp(2.6-.37*4))
# 75 percent chance they want to go to career 9 if they have a 4 response avg in apls
g <- seq(1,6,length.out=100)
plot(g, exp(2.6-.37*g)/(1+exp(2.6-.37*g)), type ="l")
```

CJ Careers 10 and 11

```
# CAREER 10
exp(-1.87+.39*4)/(1+exp(-1.87+.39*4))
# 42 percent chance they want to go to career 10 if they have a 4 response avg in apls
h <- seq(1,6,length.out=100)
plot(h, exp(-1.87+.39*h)/(1+exp(-1.87+.39*h)), type ="l")
```






```
# CAREER 11
exp(-.07+.33*4)/(1+exp(-.07+.33*4))
# 78 percent chance they want to go to career 11 if they have a 4 response avg in apls
i <- seq(1,6,length.out=100)
plot(i, exp(-.07+.33*i)/(1+exp(-.07+.33*i)), type ="l")
```