Regression Models in Terror Management Studies

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Abstract

Conventional statistical methods used in terror management theory research were assessed in order to determine possible refinements. A published article was sourced from *Frontiers in Psychology* and the accompanying primary research data was found on an open data repository. A variety of multiple linear regression models were assessed. Ordinal variables were analysed as metric, ordinal and binary data. Models that treated the ordinal data as metric either failed to detect interaction effects or inverted coefficient signs. The best fit was produced by a program developed specifically for ordinal predictor variables. Although conventional analysis methods in this field were found to be suboptimal, all valid models in this study confirmed the conclusions reported in the published article.

Introduction

Social psychology has struggled in the last few years with a “crisis in confidence” brought on by problems in replicating experimental results (Earp & Trafimow, 2015). In order to address this issue, the practice of routine data sharing has emerged. Martone and Garcia (2018) report that data sharing is becoming an integral component of modern scholarship. As a result, there are a wide variety of datasets publicly available on online repositories. The aim of this investigation was to select a set of primary research data, along with the accompanying published article, in order to examine the statistical methods used and to explore possible refinements or improvements.

Tjew-A-Sin and Koole (2018) published an article entitled “Terror management in a multicultural society” in Frontiers in Psychology and made their primary data available on the DANS data archive (DANS, 2019). The research was designed to test if a mortality salient (MS) condition produced a decrease in positive attitudes towards Muslims, immigrants and multiculturalism among native Dutch people. Terror management theory, which includes the mortality salience hypothesis, seeks to explain the reason for the existence of self-esteem and culture among humans.

Terror management theory (TMT) postulates that self-esteem and cultural world view exist to act as a buffer against the anxiety that results from conscious awareness of our own death (Pyszczynski, Solomon, & Greenberg, 2015). The theory was originally developed from the work of Earnest Becker in the 1970's (Greenberg et al., 1990) and since then there have been hundreds of studies investigating aspects of the theory, including; the mortality salience hypothesis, death-thought accessibility and the anxiety buffer hypothesis (Cox, Darrell, & Arrowood, 2019).

Tjew-A-Sin and Koole (2018) focused their attention on the mortality salience hypothesis and its effects on Dutch university students. According to the mortality salience hypothesis, when someone is primed to think about their own mortality, they will exhibit behaviours that will either bolster self-esteem or defend their cultural world view in the presence of a perceived threat. This effect is the result of an unconscious attempt to ease feelings of existential fear by reinforcing the psychological structures that buffer against it (Hart, 2019). A critical part of this hypothesis is that thoughts of mortality must be on the fringes of consciousness rather than the focus of attention (Schimel, Hayes, Williams, Jahrig, 2007).

An MS condition can be achieved using direct or indirect primes (Cox, Darrell, & Arrowood, 2019). Direct primes include questionnaires asking participants to jot down their feelings about their own death or to rate how much they agree with statements about fears relating to death. Direct primes require a delay between MS priming and the test for the response variable. This ensures that recently accessed thoughts about death are no longer the focus of attention. Indirect primes, such as conducting interviews in front of a funeral parlour (Pyszczynski, Greenberg, Solomon, Arndt, & Schimel, 2004), or in a cemetery, or flashing death related words on a screen (Cox, Darrell, & Arrowood, 2019), do not require a delay as they never become the focus of the participants attention. In a study investigating how MS effected fitness goals, it was found that fitness intentions increased for all participants if there was no delay after MS priming. After a delay, however, fitness intentions increased only for those for whom fitness was a linked to their self-esteem (Pyszczynski et al., 2004).

Tjew-A-Sin and Koole (2018) used a seven-item questionnaire about death based on the questionnaire created by Florian & Kravetz (1983) as an MS prime and a questionnaire about mood to create a delay as is typical in TMT research (Hart, 2019). The control group were primed with questions about visiting a dentist. Some critiques of TMT have suggested that the effect of the mortality salienct condition may represent general anxiety, negative emotions or worries about the future rather than anxiety about death specifically (Hart, 2019). In order to demonstrate a difference between death anxiety and other emotional responses, dental pain and other topics that induce anxiety or negative feelings are often used for the control group in TMT studies. While these alternative primes sometimes evoke a response, the size of any effect is typically less than that created by MS primes (Pyszczynski et al., 2004).

The pioneering and often cited work of Greenberg et al. (1990) established a conventional method of statistical analysis in the field of TMT that has been replicated to varying degrees in subsequent studies (Pyszczynski et al., 2004). The method of analysis in these studies involves an initial linear regression followed by a breakdown of any interaction terms that are significant. TMT studies focus on interaction terms with the mortality salience (MS) factor.

The Likert scale (Likert, 1932) is commonly used in psychology and is a standard measure in TMT research. The scale can have a range of 4, 5, 7, or 9 points where 1 typically represents the most negative response, ("strongly disagree") and the maximum level represents the most positive response ("strongly agree"). Although the data is ordinal, Likert scale data is typically analysed as though it were metric. This is especially true if multiple Likert items have been averaged in order to create a single overall response. Boone and Boone (2012) emphasize a distinction between Likert-type data, in which Likert items are assessed individually and treated as ordinal, and Likert data proper, in which responses from multiple items are combined by averaging and standardizing, and then treated as metric.

In the latter case, Boone and Boone (2012) conclude that analysis techniques and procedures designed for metric models, such as Pearson's r, ANOVA, t tests and regression models, are appropriate. This represents the analysis approach of Greenberg et al. (1990) and is a methodology that was replicated by Tjew-A-Sin and Koole (2018), who combined 49 items to create a response variable of a single value to describe a participant's overall attitude to immigration and multiculturalism. They also combined ten items to create a self-esteem variable and three items to create a national identity variable.

In order to assess whether multiple Likert items can be combined into a composite variable, a Cronbach's alpha test is often employed (Cho & Kim, 2014). If the alpha value greater than or equal to 0.7 this is an indication that there is internal consistency and that the creation of a composite variable by adding, averaging or standardizing is justified. This, however, may not be the best use of the test. (Peter, 2014).

When dealing with multiple Likert items, principal component analysis (PCA) is sometimes utilized. PCA uses linear combinations of variables to explain the variance-covariance structure of a set of variables (Johnson & Wichern, 2007). It provides a way to assess how much information each variable provides in terms of how much variability of the system it accounts for. In TMT studies, PCA loadings have be used as an indication of which variables to average together to create a composite variable. Florian & Mikulincer (1997) averaged only the items that had PCA loadings of 0.5 and above. PCA is an analysis technique for metric data but, as stated previously, Likert items are treated as metric by convention.

If a regression model indicates that an interaction term with MS is significant, further analysis of this term involves reducing the levels of each factor in the interaction to high and low scores and calculating the means for the observations occurring in each possible combination of variables. For three-way interactions there are eight possible combinations. High and low scores are achieved either by splitting the scores at the median (Florian & Mikulincer, 1997), or by using only scores that are above and below one or two standard deviations from the mean as demonstrated by Tjew-A-Sin and

Koole (2018) and Weise et al.(2012). T tests are performed to assess if the observations in any of the combinations are significantly different from the others.

Generally, the interaction terms are the only factors that are of interest in TMT studies because the focus of the research how the mortality salient condition interactions with personal characteristics such as self-esteem and cultural world view. Bassett and Connelly (2011) noted that MS was not significant as a main factor in their study and concluded that the observed increase in negativity towards immigrants in the MS condition was not due to negative mood or general anxiety.

“Simple slopes” are often created in TMT studies to assess the effect of the interaction between a single independent factor and the mortality salience condition. This is done by splitting the variable into high and low values, usually restricting data to that which is at least one or two standard deviations above or below the mean. As an example, figure 1 shows that observations with low “Right-Wing Authoritarianism” (RWA) scores in the mortality salient condition have a mean response of approximately 7. High RWA scores in the MS condition have a mean of 4.75. Dental pain in this example is the control group.

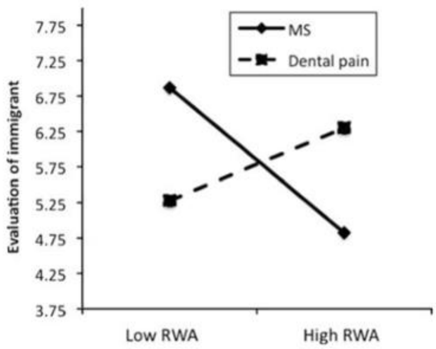

Figure 1. (Weise et al., 2012, pp. 67)

The methods detailed in this section have become standard in TMT research. While concern has been expressed about the limitations of statistical methods used in psychology overall (Sijtsma, Veldkamp and Wicherts, 2016), little has been done to explore alternative statistical methodologies in TMT studies.

Research questions to be answered in this investigation are: 1) What are the conventional analysis techniques used in TMT research? The methods employed by Tjew-A-Sin and Koole (2018) and others in the field will be explored and discussed. 2) Are the techniques used effective for the dataset in question? The quality of the model fit will be assessed. 3) Are there alternative analysis methods that are a better fit for the data? Given the vast number of possible models that could be used to describe this dataset, the focus of this study was restricted to linear regression models. And finally, 4) Tjew-A-Sin and Koole report that MS produces an effect. Is this effect present in other models? The results of valid alternative models will be compared.

The methodology section that follows describes the process undertaken to answer the research questions. It also includes a description of the software and programs that were employed. The results section details the models produced for this study. In the discussion section, the analysis techniques used by Tjew-A-Sin and Koole are assessed and the alternative models are discussed. Conclusions and references follow. Appendix A contains items pertaining to diagnostic checks and analysis results. Final thoughts appear in the conclusions section. This is followed by a list of references. Appendix B contains code and code chunks used in analysis and modelling.

Methodology

Tjew-A-Sin and Koole (2018) conducted and reported on two TMT studies. The first was complex enough to fit the scope of this project and for this reason was selected to be the focus of this analysis.

The first step was to determine what analysis methods had been used in the study and if the results reported could be replicated. The data and analysis techniques were then assessed to determine any specific challenges. After the original model was validated, other linear regression models were created for comparison. Bayesian models were of interest because prior knowledge can be incorporated into the models. Frequentist models acted as a point of comparison. Indicator variables were created as another alternative to the original model by collapsing ordinal data into dichotomous levels.

Once a variety of valid regression models had been created and assessed, the best fit for the data was reported. All valid models were assessed to determine whether they confirmed the existence of a mortality salience effect as reported by Tjew-A-Sin and Koole.

Frequentist methods used included linear regression (lm) and the generalized linear regression (glm) functions available in R (R Core Team, 2018). Model selection in frequentist models was aided by the stepAIC function in the MASS package (Ripley & Venables, 2019) and regsubsets function from the leaps package (Lumley, 2017). Model fit was assessed by residual analysis, AIC and R^2 values.

Bayesian regression models relied on code from Kruschke (2015). Altered code chunks appear in Appendix B. A metric predictor variable with multiple metric predictors model and ordinal-probit model were employed. A model selection technique created by Kruschke was also used (Appendix B.7). MCMC chains were check for representativeness, accuracy and efficiency with the diagnostic plots provided by Krusche's programs (Appendix A.1). Model fit was determined by AIC scores and multicollinearity plots.

The ordPens package (Gertheiss, 2015) was employed as a tool to create regression models with ordinal predictors. The package also contains an ANOVA (ordAOV) function to determine significance of the ordinal predictors.

Principal component analysis of ordinal data was performed by the Princals function available in the Gifi package (Mair & Leeuw, 2019).

With the exception of Princals and the ordPens package, the programs and function employed in this investigation were chosen because they were known to the author and time was not needed to learn new programs.

Results

Data Overview

Tjew-A-Sin and Koole asked 138 participants at a University in the Netherlands 10 questions to assess their self-esteem and three questions to assess how strongly they identified as Dutch. They then randomly assigned the mortality salience condition to approximately half of the participants. Mortality salience was achieved with a seven-item questionnaire about death. The control group were asked questions about their experiences at the dentist. Participants were then asked questions about their feelings towards ethnic minorities, Muslims, multiculturalism and anti-Dutch essays. The responses to 49 of these items were combined and standardized to form the response variable. A density plot of this response variable (wdefense) appears in Appendix A.2.

The responses were given on a 1 to 9 Likert scale, where higher levels indicated a more positive attitude to immigrants and multiculturalism, and lower levels indicated a more negative attitude.

Variable	Description
PCA3	Created with PCA for 5 subsets of questions then combined as one and another PCA to produce one value. Transformed PCA3: square_root[5 +(PCA3 – mean(PCA3)/std(PCA3))]
wdefense	Original variable, short for "worldview defense", averaged and standardized scores
wdefense trans	Transformed wdefense: 1/ (max(wdefense)+1-wdefense)
self-esteem	Variable indicating self-esteem score. Higher levels equivalent to higher levels of self-esteem.
national identity	Variable indicating national identity score. Higher levels indicate strong identification as a Dutch person.
se:id:ms (1)	Three-way interaction between self-esteem, national identity & mortality salience condition (1=present, 0=absent)
Self-esteem (q.i)	Individual self-esteem question (i), where i= 1,2, . . . 10
National Identity (q.i)	Individual national Identity question (i), where i= 1,2,3
mca12	Likert response data: question 12 in a subset of questions that comprised the response variable. Subject: acceptance of ethnic minorities

Table 0. Description of variables

Models

The regression results that appeared in the original research paper were replicated by using the linear regression (lm) function available in R (R Core Team, 2018). The mortality salience (MS) condition was a nominal variable coded as -1 or 1 representing the absence or presence of MS respectively. It was noted, however, that this variable had been included in the regression formula as though it were metric. Correcting the issue resulted in some small changes to the coefficients, most notably; the

Frequentist: Original		
response variable: wdefense (metric)		
independent factors: original standardized self-esteem and national identity scores & MS indicator		
Variable	Coefficient	p
Intercept	none	-
Self-Esteem	0.158	0.005
National Identity	-0.271	<0.001
se:id:ms (0)	-0.183	0.014
se:id:ms (1)	0.162	0.034
Statistics		
R-squared (regression)		0.22
AIC		280.02
Residuals Shapiro Wilk Test p-value		0.001
Residuals Non-Constant Variance Test		0.383

Table 1. Results from regression using original data.

intercept and an interaction term between self-esteem and MS were no longer significant. The results are reported in Table 1. It was apparent that the residuals of the model did not fit normality assumptions as the Shapiro-Wilk normality test produced a significant p-value. (Frequentist lm model code: Appendix B.1, Frequentist lm model diagnostics: Appendix B.2)

Two solutions were developed to address the normality issue. The first was a transformation of the response variable into a gamma distribution. To achieve this, the inverse was taken of the difference between the maximum value plus one minus the response (Table 0). The generalized linear regression function (glm) available in R (R Core Team, 2018) was used for this data. The results of which are displayed in Table 2. Residual diagnostic plots appear in Appendix A.3. (Frequentist glm code: Appendix B.1, Frequentist glm model diagnostics: Appendix B.3). The generalized linear model appears to fit the data much better than the first attempt as an AIC score of -276.5 is a significant improvement on the 280 score of the previous model. The interaction term is behaving in an unexpected way as the presence of MS causes a change in the response variable in the same direction as the self-esteem coefficient. Increased self-esteem is reported to increase positive feelings towards an outgroup whereas MS is associated with increasing negativity towards outgroups (Cox, Darrell & Arrowood, 2019).

Frequentist: wdefense metric		
response variable: wdefense trans (metric)		
independent factors: original standardized self-esteem and national identity scores & MS indicator		
Variable	Coefficient	p
Intercept	0.371	<0.001
Self-Esteem	0.021	0.005
National Identity	-0.038	<0.001
se:id:ms (0)	-0.027	0.006
se:id:ms (1)	0.021	0.054
Statistics		
Dispersion Parameter		0.072
AIC		-276.51
Residual Deviance: Reduced Model		7.7956 (133 df)
Residual Deviance: Full Model		7.8763 (130 df)

Table 2. Results using variable wdefense tran and glm function

The second solution to the violation of the normality assumption was to create a new response variable using a principal component analysis specifically designed for categorical data. The Princals function, available as part of the Gifi package in R (Mair & Leeuw, 2019), was used to reduce the results of 48 Likert-type items into a single measure of attitudes towards immigrants, Muslims and immigration (Appendix B.4). Components that accounted for at least 70% of the variation in the five themed subsets of questions were combined into a larger PCA. The resulting response variable (PCA3) was transformed for better model fit by adding 5 to the standardized value and taking the square root. This transformed variable was strongly and negatively correlated with the original response variable. The Pearson's correlation coefficient was -0.9 (Appendix A.4). The AIC score of -38.14 was a significant improvement on that of the original model but not as good as the model in Table 2. Once again, the signs of the coefficients for the interaction terms are not in line with what has been reported in the literature (Pyszczynski, Greenberg, Solomon, Arndt & Schimel, 2004). The interaction terms are borderline significant. If they are removed, the AIC score increases to -34.66. (model diagnostic plots: Appendix A.5)

Frequentist: PCA3 metric		
response variable: PCA3 trans (metric)		
independent factors: original standardized self-esteem and national identity scores & MS indicator		
Variable	Coeffiecient	p
Intercept	2.223	<0.001
Self-Esteem	-0.063	<0.001
National Identity	0.065	<0.001
se:id:ms (0)	0.044	0.058
se:id:ms (1)	-0.046	0.055
Statistics		
R-squared (regression)		0.1883
AIC		-38.14
Residuals Shapiro Wilk Test p-value		0.2
Residuals Non-Constant Variance Test		0.08

Table 3. Regression using response variable created with Princals

Terror management theory has become a large, well-developed field of study. Bayesian models have the capacity to incorporate prior knowledge into regression models. In order to explore the possible benefits of this a Bayesian model with vague priors was created along with three further models that incorporated moderately strong priors for self-esteem and national identity individually and combined. Code from Kruschke (2015) was modified to achieve this (Appendix B.5). MCMC chains were checked as demonstrated in Appendix A.1. No multicollinearity was present (Appendix A.6). Table 4 shows that the interaction term was borderline significant when the priors were vague and when self-esteem alone had a strong prior (Model 1 and 2 respectively). Models that included a strong prior for national identity had interaction terms that were significant. However, as with other models that used the original independent variables, the sign of the interaction coefficient was in the same direction as self-esteem rather than national identity as expected.

Bayesian: PCA3 models												
response variable: PCA3 trans (metric) independent factors: original standardized self-esteem, national identity scores & MS condition												
Model 1				Model 2			Model 3			Model 4		
Weak prior for self-esteem & national identity Zmean: 0, precision: 0.0001				Moderately strong prior for self-esteem Z mean: -1.5, precision: 50			Moderately strong prior for national identity Z mean: +1.5, precision: 50			Moderately strong prior for self-esteem & national identity se Z mean: -1.5, id Zmean: +1.5, se & id precision: 50		
Variable	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound
Intercept	2.224	2.21	2.23	2.22	2.21	2.24	2.22	2.21	2.24	2.22	2.21	2.24
Self-Esteem	-0.062	-0.097	-0.025	-0.134	-0.17	-0.101	-0.063	-0.1	-0.024	-0.144	-0.183	-0.108
National Identity	0.064	0.03	0.1	0.064	0.026	0.103	0.14	0.106	0.179	0.15	0.11	0.189
se:id:ms (1)	-0.045	-0.091	0.001	-0.047	-0.095	0.003	-0.072	-0.122	-0.023	-0.079	-0.134	-0.022

Table 4. Bayesian Models with strong and weak priors.

TMT studies assess the effects of independent factors in terms of low and high values. As such, indicator variables representing high and low self-esteem scores, and high and low national identity scores, were created to test in Bayesian and frequentist models. The median of each individual question used to create the original predictors was calculated. In the same manner as Florian and Mikulincer (1997), values below the median were classed as low scores and values equal to or greater than the median were classed as high scores. Previous research predicts an effect in the MS condition when self-esteem is low and national identity is high. The indicator variables were coded to reflect this information: low self-esteem scores and high national identity scores were coded as 1.

The regression formula contained fourteen indicator variables as predictors; ten self-esteem questions, three national identity questions and the mortality salience indicator. Given the number of variables, model selection techniques were employed to determine the best combinations. In frequentist models the process was aided by the stepAIC function in the MASS package (Ripley & Venables, 2019) and regsubsets function from the leaps package (Lumley, 2017) (Appendix B.6). In Bayesian models, a delta variable was used that acted as a switch to include or exclude variables as demonstrated by Kruschke (2015). The code was written so that the probability of each combination of variables was reported (Appendix B.7).

The significant independent factors in both the Bayesian and frequentist models were self-esteem question 3, national identity question 3 and the interaction term between self-esteem, national identity and MS. Multicollinearity was a significant issue in all Bayesian models with indicator variables, including those using a gamma distribution (Appendix A.7 & B.8). In order to mitigate this, the intercept was removed from all but Model 5 (Table 5). Bayesian models using the gamma distribution were created for the transformed wdefense variable but are not discussed here because they produced similar information and were subject to the same issues.

Interestingly, the interaction coefficient is negative while the other factors are positive in Model 4. The PCA3 response variable is negatively correlated with the original, therefore a negative coefficient indicates a more positive attitude towards immigrants. As low self-esteem and high national identity are coded as 1, the regression reports that both have a negative impact on attitudes towards

Bayesian: PCA3 indicator models															
response variable: PCA3 trans (metric) independent factors: indicator variables															
	Model 1			Model 2			Model 3			Model 4			Model 5		
	Weak prior for self-esteem & national identity Zmean: 0, precision: 0.0001			Moderately strong prior for self-esteem Z mean: +1.5, precision: 50			Moderately strong prior for national identity Z mean: +1.5, precision: 50			Moderately strong prior for self-esteem & national identity Z mean (se & id): +1.5, precision (se&id): 50			weak priors		
Variable	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound
Intercept	none	-	-	none	-	-	none	-	-	none	-	-	2.2	2.16	2.24
Self-esteem (q.3)	0.102	0.024	0.177	0.263	0.176	0.358	0.11	0.017	0.207	0.402	0.304	0.501	-	-	-
National Identity (q.3)	0.13	0.057	0.2	0.147	0.067	0.234	0.283	0.206	0.361	0.384	0.296	0.469	-	-	-
se:id:ms (1)	-	-	-	0.038	-0.129	0.195	0.08	-0.084	0.237	-0.189	-0.374	-0.002	0.312	0.189	0.425

Table 5. Bayesian models using indicator variables with strong and weak priors

immigrants, as predicted. However, the interaction term with MS should have an effect in the same direction. Model 5 contains only the interaction term which has an effect that is in the same direction as low self-esteem and high national identity (as expected) and is approximately three times that of the main factors in Model 1 with vague priors. This is likely due to problems with multicollinearity.

A frequentist model was also constructed using the indicator variables. Multicollinearity was again a problem. Model 1 in Table 6 which includes two main factors only; self-esteem and national identity, has an AIC score of -29.4. The model with just the three-way interaction term has an AIC score of -38.04, very similar to the AIC score of the same model with the original predictor variables. The

Frequentist: PCA3 indicator				
response variable: PCA3 trans (metric)				
independent factors: indicator variables				
Model 1			Model 2	
Variable	Coefficient	p	Coefficient	p
Intercept	2.125	<0.001	2.2	<0.001
Self-esteem (q.3)	0.105	0.009	-	-
National Identity (q.3)	0.128	<0.001	-	-
se:id:ms (0)	removed due to multicollinearity	-	-	-
se:id:ms (1)			0.31	<0.001
Statistics				
R-squared (regression) p-value		0.11	0.152	
AIC		-29.42	-38.04	
Residuals Shapiro-Wilk Test p-value		0.086	0.14	

Table 6. Frequentist models with indicator variables

coefficients were essentially the same as those of the indicator variables in the Bayesian models. Density plots of the residuals support the conclusion that the interaction-only model is a better fit (Appendix A.8).

Ordinal-probit models are regression models designed for ordinal response variables. Although the response variable in this case was a composite, analysing individual response items separately may be a useful alternative method. The distributions of the forty-eight response items were analysed to determine which would be appropriate to use as an example. The specific ordinal-probit model used was written by Kruschke (2015) and assumes a latent normal distribution (Appendix A.5). This is an example of a cumulative ordinal-probit model in which a continuous distribution underlies categorical factor levels (Bürkner & Vuorre, 2019). Item mca12 was selected because it appeared to represent a normal distribution (Appendix A.9). The specific question was not included with the data, but it was regarding the acceptance of ethnic minorities on a scale of 1 to 9 with 9 the most accepting and 1 the least. The best fit was the three-way interaction term between low self-esteem, high national identity and MS. The advantage of this model was that it was easy to interpret. The intercept term was 6.1 which was reasonable because the median of mca12 was 6. The interaction coefficient was -3.24 which suggests a loss of approximately three points in for people with low self-esteem and high national identity in the presence of MS. The AIC score was 582, far greater than the AIC of other models with the PCA3 response variable (Appendix B.10 for manual AIC calculation). The interaction term between low self-esteem and high national identity in the absence of MS was not significant.

Ordinal-Probit Model			
response variable: mca12 (ordinal) independent factors: indicator variables			
Weak prior for self-esteem & national identity Zmean: 0, precision: 0.0001			
Variable	Coefficient	95% HDI Lower Bound	95% HDI Upper Bound
Intercept	6.1	5.53	6.58
se:id:ms (1)	-3.24	-4.57	-1.86
AIC	582		

Table 7. Ordinal-Probit model for response variable mca12

Liddell and Kruschke (2018) ran simulations to show that treating ordinal data as metric produces systematic errors, namely underestimating effects, false positives and the inversion of means. The latter became a point of interest as it may explain why the interaction coefficients in the metric models indicated that the MS condition increased positive feelings towards immigrants rather than decreasing them as expected.

In order to explore this further, the ordinal response variable from the previous model, item mca12, was used to compare ordinal-probit and metric models. Six models were created, both Bayesian and frequentist. Independent variables were either indicator variables or individual Likert-type items treated as metric. The specific variables used were national identity question 3 and the interaction term between MS and self-esteem question 2. This was the one combination of predictors that was able to create valid models across all six model types.

The results appear in Table 8. Very little variation was evident between models created with indicator variables (Frequentist 2, Bayesian 3 and Bayesian 4) and the interaction coefficients were the same sign as the national identity variable as expected. Models that treated the predictors as metric (Frequentist 1, Bayesian 1 and Bayesian 2) produced results that were far more varied. The intercept values ranged between 5.25 and 9.59. The interaction coefficients were either significant in the wrong direction (increasing acceptance to ethnic minorities) as with Frequentist 1 or not significant in Bayesian 1 and 2. Treatment of the response variable as metric or ordinal did not appear to impact the results. The AIC scores ranged between 581 and 591. Interestingly, these scores are comparable to the AIC score of the ordinal-probit model that used the PCA3 response variable.

	Model					
	Frequentist 1	**Bayesian 1**	**Bayesian 2**	**Frequentist 2**	**Bayesian 3**	**Bayesian 4**
Response Var. **Independent Vars.**	metric metric	metric metric	ordinal metric	metric indicator	metric indicator	ordinal indicator
Intercept	5.25	8.83	9.59	6.54	6.47	6.68
CI 2.5% **CI 97.5%** **p value**	2.67 7.83 < 0.001	7.2 10.4 na	7.68 11.6 na	5.91 7.16 < 0.001	6.01 6.93 na	5.91 7.35 na
National Identity	-0.47	-0.43	-0.52	-0.95	-0.93	-1.11
CI 2.5% **CI 97.5%** **p value**	-0.67 -0.27 < 0.001	-0.64 -0.22 na	-0.8 -0.29 na	-1.64 -0.26 0.007	-1.62 -0.23 na	-1.83 -0.25 na
Interaction: self-esteem/mortality salience (1)	0.49	not sig	not sig	-1.32	-1.27	-1.33
CI 2.5% **CI 97.5%** **p value**	0.19 0.8 0.002	- - na	- - na	-2.14 -0.5 0.002	-2.08 -0.53 na	-2.29 -0.51 na
Interaction: self-esteem/mortality salience (0)	0.53	-	-	-	-	-
CI 2.5% **CI 97.5%** **p value**	0.22 0.84 0.0009	- - -	- - -	- - -	- - -	- - -
AIC	581.2	588.72	590.29	590.6	590.4	591.09

Table 8. Comparison of ordinal and metric models. Response variable: item mca12. Predictors: national identity q.3 and the interaction term between self-esteem q.2 and mortality salience.

Finally, the PCA3 transformed response variable created with Princals (Mair & Leeuw, 2019) was used in conjunction with the ordPens package (Gertheiss & Tutz, 2009) to produce a model that treated all variables as ordinal while avoiding the possibility of losing information through the creation of indicator variables.

The ordPens package includes an ANOVA function (ordAOV) (Appendix B.11) to test the significance of the ordinal variables. The significant ordinal variables were self-esteem question 3 and national identity question 3 as with previous models. Self-esteem question 2 and national identity question 2 had to be removed from the data because they did not fit the requirements of the function. In order to be included each possible level from 1 to the maximum must be present.

The interaction term was created by labelling the different combinations of the indicator variables from 1 through 8 and then manually ascribing each observation a number to represent the combination. The subsequent smoothed coefficients produced by the ordSmooth function (Appendix B.11) appear in Figures 2 and 3. Each line these of plots indicates the coefficients for five different penalty levels between 60 and 400. A penalty of 200 created a model with the best AIC score (-38.4). Residual analysis met assumptions (Appendix B.12 and Appendix A.10). Increasing levels for self-esteem question 3 are associated with decreasing coefficients as shown in Figure 2. As PCA3 is negatively correlated with the original response variable, this indicates that higher self-esteem levels are associated with more positive attitudes towards immigrants, as expected. National identity has the opposite effect; increasing levels are associated with more positive coefficients (Figure 3). The interaction coefficient was 0.023 which is equivalent to approximately national identity levels 4 and 5. (Appendix A.12). The ordPens package produces a model that fits the data well and is in keeping with the expected results according to the relevant literature.

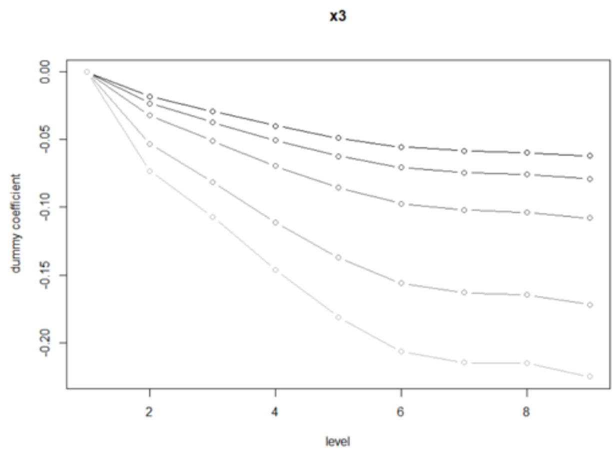

Figure 2. Coefficients for self-esteem q3.

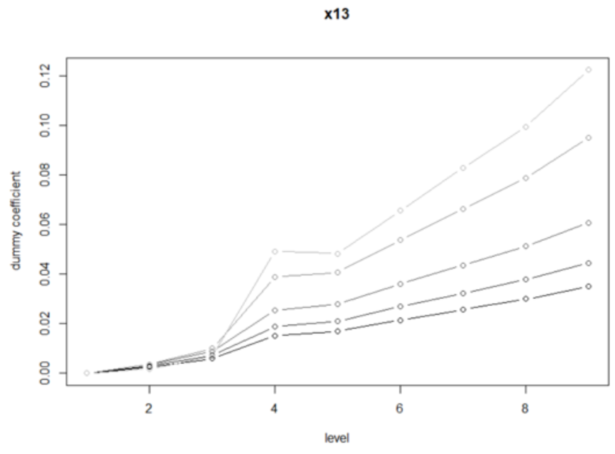

Figure 3. Coefficients for national identity q.3.

Discussion

Tjew-A-Sin and Koole (2018) conducted a study to determine the effects of mortality salience in order to add a European perspective to the growing body of work in TMT research. Their analysis was typical of its field in that a regression model was constructed to determine the significance of any interaction coefficients. Despite reporting the results of a regression model that did not meet assumptions and was therefore invalid, their conclusion agreed with the multiple valid models tested in this investigation. The reason they were able to overcome the limitations of their model was that their analysis ultimately relied on the use of indicator variables. They created indicators by splitting the data above and below one standard deviation from the mean. Regardless of the problematic use of standard deviations with ordinal data, the resulting high/ low independent variables achieved an effect similar to splitting the data at the median. Observations were separated into the eight combinations of the indicator variables and mean responses of each of these interaction combinations were calculated.

Dolnicar and Grün (2007) report that a number of studies which looked at the effect of reducing ordinal data to dichotomous levels concluded that there was no significant difference between the collapsed and original data. Tjew-A-Sin and Koole’s indicator variables were created by removing the data within one standard deviation from the mean, and as such some loss of information was inherent in the process. However, this “loss” may also have been an effective way to extract the most pertinent data for analysis. The ways in which indicator variable creation methods might impact statistical outcomes was not explored in this investigation. Models created with indicator variables (Table 5, Table 6, Appendix A.7) exhibited problems with multicollinearity, particularly in the presence of interaction terms. It was an issue observed in both Bayesian and frequentist methods.

Tjew-A-Sin and Koole analysed ordinal data with metric techniques, as is the convention in TMT studies. Beyond the initial regression, they employed ANOVAs, t tests, standard deviations and further regressions for data subsets.

Liddell and Kruschke (2018) highlighted three systematic errors that occur when using metric models with ordinal data; detecting an effect where none exists (type 1 error), failure to detect an effect (type 2 error), and the inversion of effects. The interaction coefficients listed in Table 8 provide some evidence to support this finding. The effect of the interaction is negative in models that used indicator predictors and either positive or insignificant in models that treated ordinal predictors as metric. The effect size of the positive coefficient in one model is much less than the effect sizes of the negative coefficient. Bürkner and Vuorre (2019) also report that effect size estimates can be distorted by size and certainty when using metric models with ordinal data.

Although the conclusions reached may be similar between ordinal and metric models, Bürkner and Vuorre (2019) assert that prediction utility is much greater for ordinal models as they are not dependent on incorrect assumptions about the distribution.

Changes in the number of Likert scale levels and level descriptors can alter the results (Tian, Huang, Cheng & Zhang, 2018) due to scale invariance between adjacent categories (Dolnicar & Grün, 2007). One metric variable was included in the responses collected by Tjew-A-Sin and Koole. It was a question asking participants to report their feelings of warmth towards Muslims on a sliding scale from zero to one hundred. On the surface, this may appear a viable alternative to ordinal data, however, as Dolnicar and Grün (2007) point out, a metric variable may be easier to analyse but it might not be a more accurate representation of how the concepts are structured in a person’s mind.

Another popular analysis technique in TMT research, also employed by Tjew-A-Sin and Koole, was the use of Cronbach's alpha to justify averaging several Likert-type items to create a single variable. In this case, as stated previously, 49 items were combined to produce the response variable, 10 items for the self-esteem variable and three for the national identity variable.

Cronbach's alpha is taken as a measure of the internal consistency of a set Likert-type items, that is the capacity of set items to estimate the same underlying concept. According to Cho and Kim (2014) and Peters (2014), the alpha measure is unrelated to both internal consistency and the reliability of a scale. Recommended alternatives include the "Greater Lower Bound" or the Omega (Peters, 2014).

Another option would be to use just one Likert-type item for each variable. For example, Brailovskaia and Margraf (2018) reported that the single item self-esteem scale (SISE) was a reliable predictor of the Rosenberg ten-question self-esteem quiz.

With this in mind, ordinal-probit models were created using a single Likert-type item: mca12. The most probable model, as selected by Kruschke's delta method (Appendix B.7), appears in Table 7. It contains only the intercept and a three-way interaction coefficient. The AIC score is 582 which is less than other models with the same data (for example, Bayesian 4 in Table 8). The coefficients in this model are easy to interpret. The intercept was very close to the median. The interaction coefficient can be read as the number of levels the expected response decreases in the presence of low self-esteem, high national identity and mortality salience. The ease of interpretation of ordinal models has been noted by others including Bürkner and Vuorre (2019).

The fact that the model contained only interaction terms may be a problem according to Rouder, Engelhardt, McCabe and Morey (2016), who recommend that such models are excluded from consideration. Their rationale is that these models assume that interactions perfectly cancel out main effects, which is implausible. They also state that models with only main factors should be excluded when the dependent measure is ordinal. In this situation, the effect of one independent factor does not depend on the value of another and additivity is therefore not a meaningful concept.

Rouder et al. (2016) propose the use of cornerstone parameterization to create valid interaction-only models. An alternative parameterization can produce a model that does not rely on the perfect balance assumption. Unfortunately, there was not time to explore this technique before the completion of this paper. However, Rouder et al. (2016) were able to provide an example of cornerstone parameterization using a mortality salience study. They demonstrated the use of reparameterization to confirm a significant MS effect. Conventional analytical techniques had also concluded that the effect was significant, but Rouder et al. (2016) argue that their model was theoretically sound and hence an improvement on the original. This work is important as many TMT studies report models in which mortality salience is significant only as part of an interaction term and not as a main factor (Pyszczynski et al., 2004).

While there are many options for modelling ordinal response variables, options for ordinal predictor variables are limited despite their ubiquitous use in psychology, sociology, biomedical research and others (Tian, Huang, Cheng & Zhang, 2018). One such option is the ordPens package (Gertheiss, 2015) which, in combination with the Princals function (Mair & Leeuw, 2019), produced the best results in this study; achieving a competitive AIC score (-38.4) while treating ordinal data as ordinal. The best AIC score was by far that of the gamma distribution model in Table 2 at -276.5. In this model the data was treated as metric and, as has been previously discussed, the prediction utility is likely to be decreased as a result.

The Princals ANOVA function (ordAOV) requires that every factor level of the ordinal variables occurs at least once in the data. There were two variables in the dataset that did not meet this requirement: questions 2 and 12 (self-esteem question 2 and national identity question 2 respectively). These variables had strong correlations with questions 3 (self-esteem) and 13 (national identity) so removing them from the model did not present any concerns about a loss of model accuracy.

The ordAOV function is only able to check the significance of ordinal variables. The interaction term was included in this model as a nominal variable and was not checked for significance in the presence of the other variables. The inclusion of the interaction term reduced the AIC score significantly (it was over 1000 without it) and the residual analysis showed that the model met assumptions. It was therefore kept in the model. The interaction coefficient representing low self-esteem and high national identity in the mortality salient condition and the national identity coefficient were positive indicating a decrease in positive attitudes towards immigrant as expected. In a similar model with the PCA3 response variable and indicator variables (Bayesian Model 4 with strong priors, Table 5), the interaction coefficient was negative and thus indicated an increase in positive attitudes towards immigrants. The ordPens model appears to have been able to handle the inclusion of the interaction term in a way that others could not.

Computational programs, functions and other techniques that fit ordinal data to regression models are available. They are not currently in use in TMT research. More appropriate statistical methodologies are not necessarily accessible to non-statisticians as they are likely to not be taught in university programs, tend to be discussed in highly technical papers and might involve computation packages and functions that do not provide neat, easily interpretable, tabulated results. Once conventional methods have been established, change can be difficult as editors and other researchers come to expect results to be reported in a certain way. As such, Sijtsma, Veldkamp and Wicherts (2016) recommend greater collaboration with statisticians to ensure the use of appropriate models. They also believe that increasing the involvement of statisticians in psychology research encourages the development of novel solutions to statistical problems specific to certain fields.

This study was limited to the analysis of regression model fits to a dataset. A wide range of alternatives analysis options are available and were beyond the scope of this investigation. The specific functions used to create models were selected because of their familiarity to the author (with the exception of Princals and the ordPens package). As such there may be newer and improved functions for performing the same tasks.

Conclusions

Conventional statistical methodologies in TMT studies are not appropriate for the data that are collected. As expressed by Liddell and Kuschke (2018), Bürkner and Vuorre (2019), Tian, Huang, Cheng and Zhang (2018), Dolnicar and Grün, (2007), and many others: Ordinal variables should not be treated as metric. Conventions, however, can be difficult to change.

The ordPens package (Gertheiss, 2015) produced a good model of the dataset provided by Tjew-A-Sin and Koole (2018). The AIC score was lower than other models and the results were in keeping with prior knowledge about the effects or mortality salience. A composite response variable was created with Princals (Mair & Leeuw, 2019), a function that performs principal component analysis on categorical variables. Self-esteem question 3 and national identity question 3 were significant, as well as a three-way interaction term between self-esteem, national identity and mortality salience.

Ordinal-probit models were created using item mca12 as the response variable. The results were easy to interpret and showed a significant decrease in acceptance of ethnic minorities in the presence of low self-esteem, high national identity and mortality salience, as predicted. However, reparameterization is likely necessary as this is an interaction-only model which assumes levels are perfectly chosen so that main effects cancel.

All of the valid models created in this study confirmed that the effect of mortality salience is significant.

Further investigations might include an examination of how the specific method for creating indicator variables impacts regression model outcomes. The use of cornerstone reparameterization and its effects in ordinal-probit models could be another avenue for investigation. An exploration of modelling methods beyond linear regression would be useful, particularly if there are models that ease to create and interpret.

Vergani, O'Brien, Lentini and Barton (2019) note that TMT research has been tackling problems that pose significant security risks, such as why people are drawn to extremism and violence. As a result, they state, it is important that methodological and theoretical limitations of modelling used in TMT studies are overcome.

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APPENDIX A

A.1: MCMC chain diagnostics: 1) Good mixing apparent in top left plot. 2) Effective Sample Size (ESS) at least 10,000. 3) Shrink factor smaller than 1.1. 4) Density plots of three chains closely overlap.

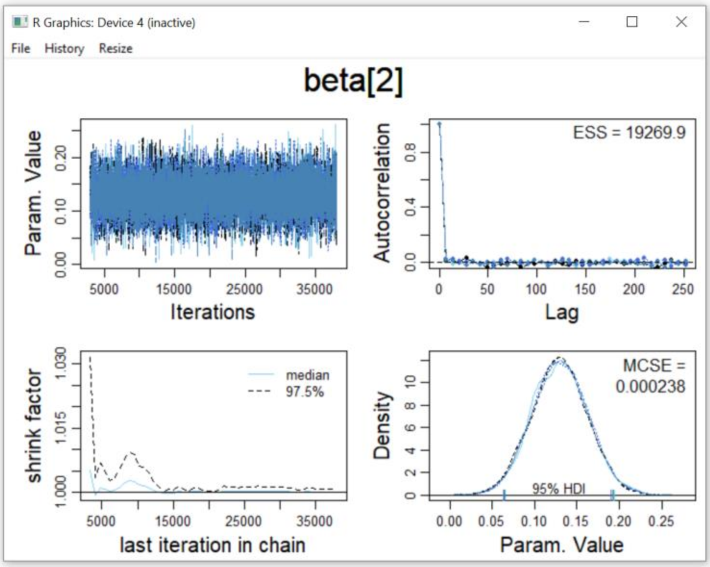
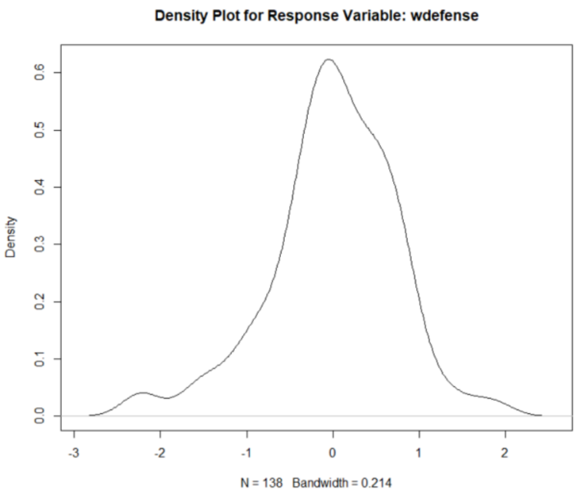


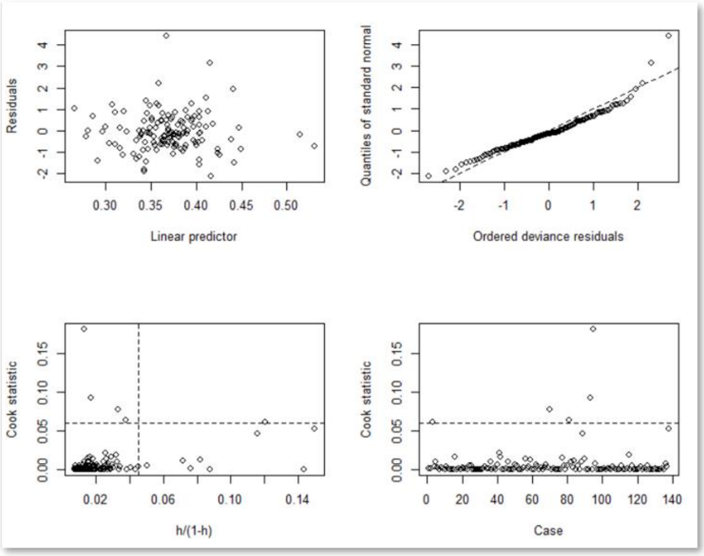
Figure A.1. Example of MCMC chain diagnostics for variables in Bayesian models.

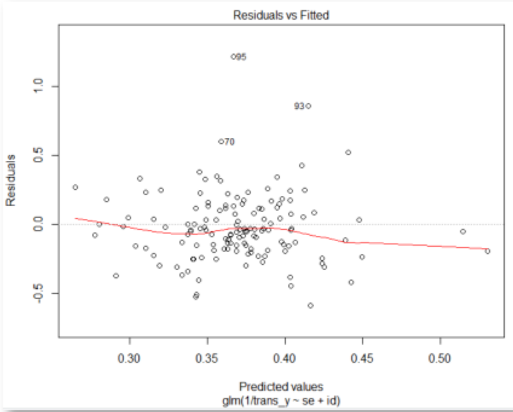
A.2: Density plots for original response variable



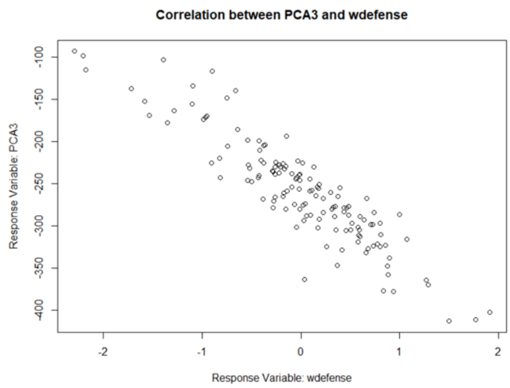
A.3: Residual analysis for model in Table 2

Deviance residuals in the QQ plot follow the reference line. A couple of outliers though they do not appear significant as no observations fall completely into the top right box in the Cook's statistic box. The red line running through the Residual vs. Fitted plot is relatively straight, no distinct pattern observable in the observations.

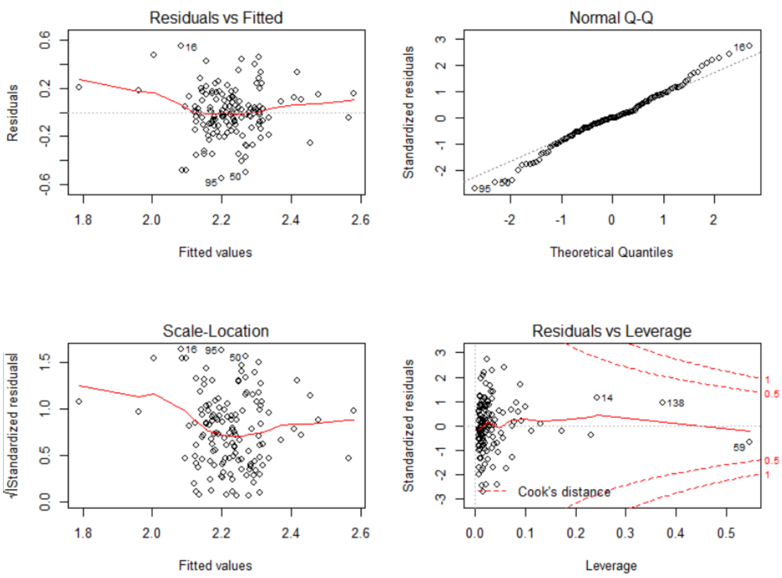




A.4: Correlation between PCA3 and wdefense response variables

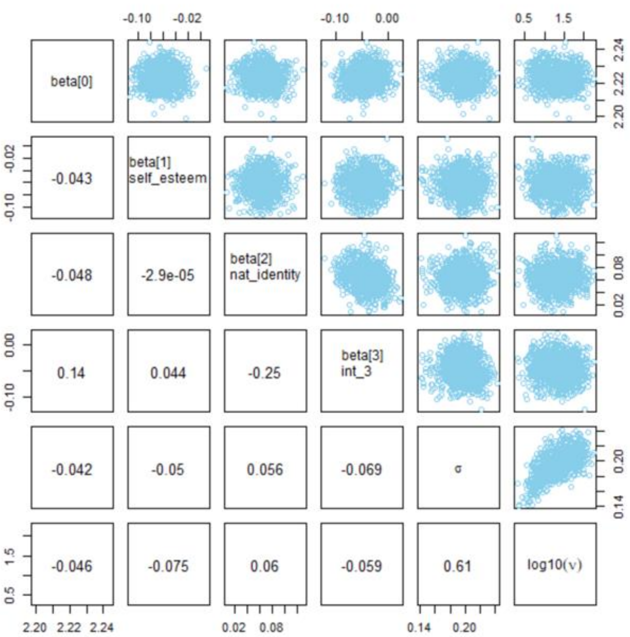


A.5: Residuals for model in Table 3

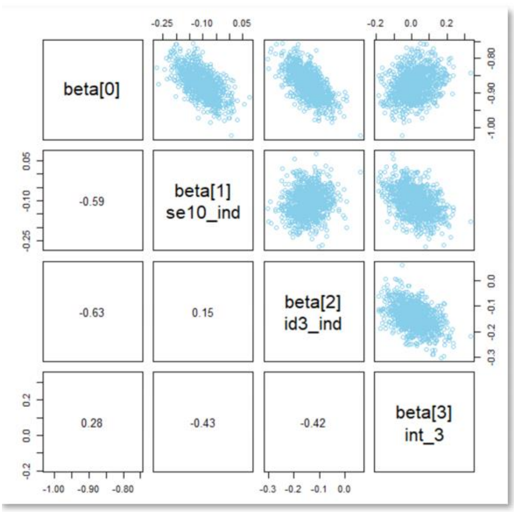


A.6: Example of multicollinearity check for models in Table 4

Minimal correlation observed between variables.



A.7: Examples of multicollinearity issues from models in Table 5 and Bayesian Models with gamma pdf



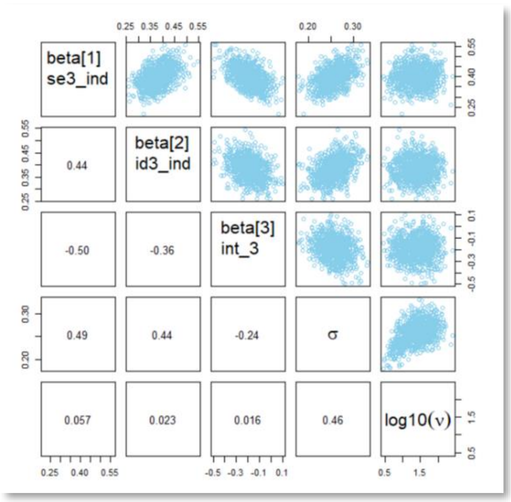
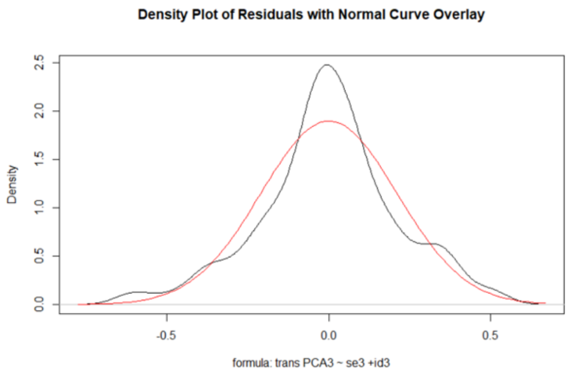


Figure A.7.1. Bayesian model with indicators wdefense (gamma dist)

Figures A.7.2. Indicator models with PCA3 and strong priors

A.8: Density plots of residuals for models in Table 6



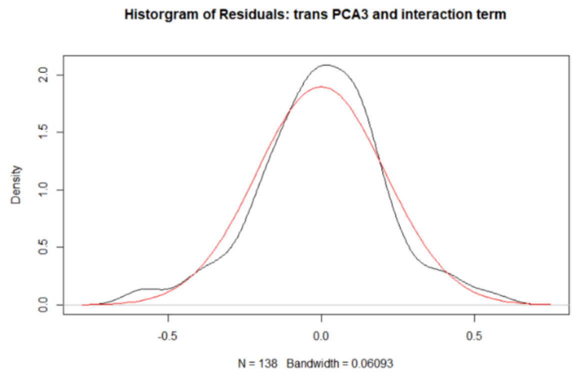
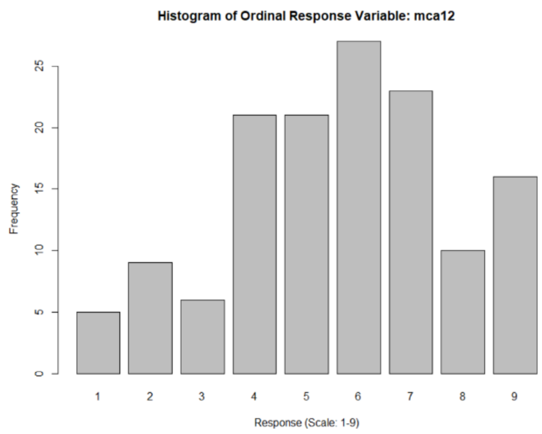


Figure A.8.1. Main factors only

Figure A.8.2. Interaction term only

A.9: Distribution of item mca12



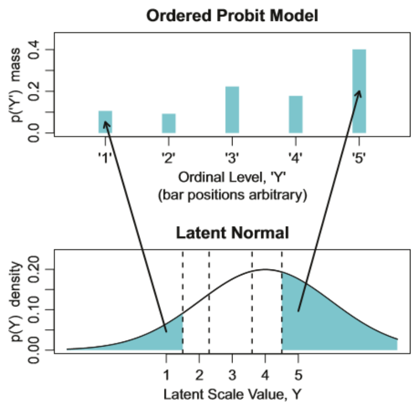
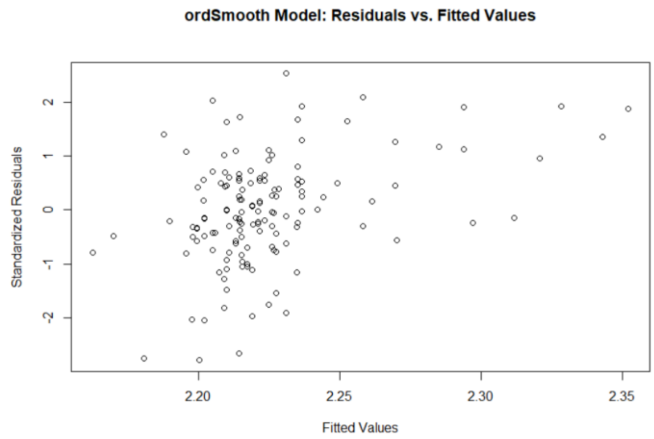
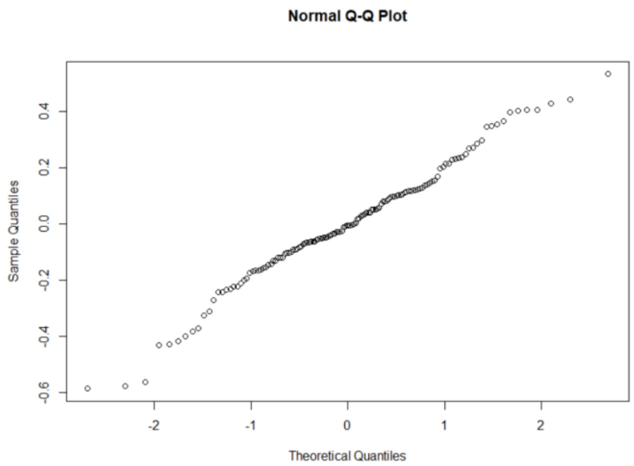


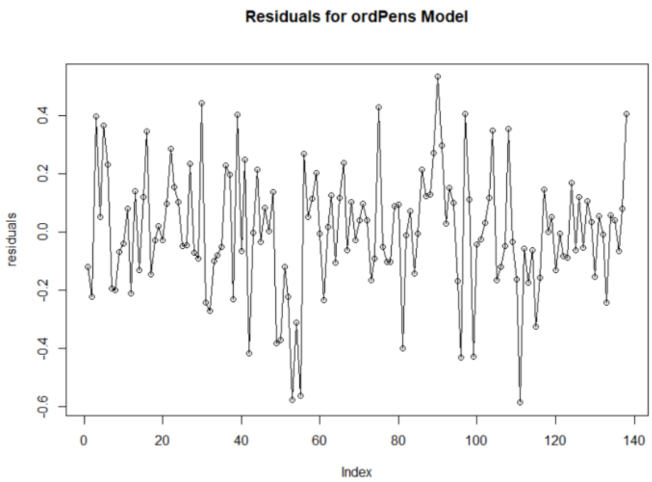
Figure A.9.1. Histogram of item mca12

Figure A.9.2. How categorical variables represent a latent normal distribution (Liddell & Kruschke, 2018, p.329)

A.10: ordPens function residual plots







A.11: ordPens function results

	400	300	200	100	60
intercept	2.251	2.258	2.270	2.299	2.324
x3:1	0.000	0.000	0.000	0.000	0.000
x3:2	-0.018	-0.023	-0.031	-0.051	-0.070
x3:3	-0.029	-0.036	-0.049	-0.077	-0.100
x3:4	-0.039	-0.049	-0.067	-0.105	-0.136
x3:5	-0.048	-0.061	-0.083	-0.130	-0.169
x3:6	-0.054	-0.069	-0.094	-0.148	-0.193
x3:7	-0.057	-0.072	-0.098	-0.154	-0.200
x3:8	-0.058	-0.073	-0.100	-0.155	-0.200
x3:9	-0.061	-0.077	-0.104	-0.162	-0.209
x13:1	0.000	0.000	0.000	0.000	0.000
x13:2	0.002	0.003	0.003	0.003	0.000
x13:3	0.006	0.007	0.008	0.009	0.005
x13:4	0.015	0.019	0.025	0.037	0.047
x13:5	0.017	0.021	0.027	0.039	0.046
x13:6	0.021	0.026	0.035	0.052	0.062
x13:7	0.025	0.032	0.042	0.063	0.079
x13:8	0.029	0.037	0.049	0.075	0.093
x13:9	0.034	0.043	0.059	0.090	0.114
U1:1	0.000	0.000	0.000	0.000	0.000
U1:2	-0.003	-0.004	-0.006	-0.011	-0.016
U1:3	-0.001	-0.001	-0.002	-0.003	-0.003
U1:4	0.013	0.017	0.023	0.038	0.051
U1:5	-0.003	-0.003	-0.004	-0.005	-0.005
U1:6	0.003	0.004	0.006	0.010	0.015
U1:7	-0.002	-0.003	-0.004	-0.007	-0.009
U1:8	0.001	0.000	-0.001	-0.006	-0.014

APPENDIX B

B.1: Frequentist models

```
setwd("~/Minor_Thesis/terror_management")
msd <- read.csv("study_1_MS_analysis_spread.csv")

y <- msd$PCA3 # wdefense
u <- mean(y)
std <-sd(y)
std_y <- (y-u)/std
trans_y <- sqrt(5+std_y)
#trans_y <- 1/(max(y)+1-y) # wdefense
# frequentist lm model with original predictors:
lm_model <- lm(trans_y ~ se + id + factor(ms):se:id ,data=msd)
# frequentist lm model with indicator predictors:
lm_model <-
lm(trans_y~factor(x1)+factor(x2)+factor(x3)+factor(x4)+factor(x5)+factor(x6)+factor(x7)+
                    factor(x8)+factor(x9)+factor(x10)+factor(x11)+ factor(x12)+factor(x13)+
                    factor(x14), data=msd)
# frequentist glm model with indicator predictors:
glm_model <-glm(trans_y~factor(x1)+factor(x2)+factor(x3)+ factor(x4)+factor(x5)+factor(x5)+
        factor(x6) + factor(7) + factor(8) + factor(9) +factor(10)
+factor(11)+factor(12)+factor(13)+factor(14), family=Gamma(link=”identity”), data=msd)
summary(lm_model)
anova(lm_model)
```

B.2: Frequentist lm model diagnostics

```
library(car)
shapiro.test(residuals(model)) # normality test
ncvTest(model) # non-constant variance test
durbinWatsonTest(model) # autocorrelation test
AIC(model)
car::vif(model) # variance inflation indicators (vif)
ur <- mean(residuals(model))
stdr <- sd(residuals(model))
stdr
std_r <- (residuals(model)-ur)/stdr
plot(density(std_r), main="Standardized Residuals with Normal Curve Overlay",
   xlab="Formula: y ~ x2 + x13")
curve(dnorm(x, mean=0,sd=1.9),col=10, add=TRUE)
par(mfrow=c(2,2))
Residual plots:
plot(model, which=1)
plot(model, which=2)
plot(model, which=3)
plot(model, which=5)
par(mfrow=c(1,1))
plot(residuals(factor14), type="o", main="Residuals", ylab="Residuals from Model: y ~ se2 +
indent3")
```

```
abline(h=0, col='red')
```

B.3: Frequentist glm model diagnostics

```
pchisq(model$deviance, df=model$df.residual, lower.tail=FALSE)
dev_res <- residuals(model, type='deviance') # type= pearson or deviance
plot(dev_res, type='o')# autocorrelation
abline(h=0, col="red")
plot(dev_res ~ factor14$fitted.values)
qqnorm(dev_res)
qqline(dev_res)
plot(density(dev_res),main="Density Plot Deviance Residuals")
library(boot)
glm.diag.plots(factor14, glmdiag = glm.diag(factor14))
anova(model, complex_model, test="Chi")# test of significance between two models
```

B.4: Princals (Categorical Principal Component Analysis from Gifi package in R)

```
library(Gifi)
likert_matrix <- msd[,5:53]
fitord <- princals(likert_matrix, ndim=10)
fitord
summary(fitord)
plot(fitord, plot.type = "transplot")
plot(fitord, "loadplot", main = "Loadings Plot se10 Data")  ## aspect ratio = 1
plot(fitord, "biplot", labels.scores = TRUE, main = "Biplot ABC Data")
plot(fitord, "screeplot")
```

B.5: Code for Bayesian models in Table 4 (Response variable PCA3 and the original independent variables)

Kruschke, J.K. (2016). DBDA2E-utilities.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

Altered coded chunk from:
Kruschke, J.K. (2016). Jags-Ymet-XmetMulti-Mrobust-Example.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
myData = read.csv( file="study_1_MS_analysis_spread.csv" )
y <- myData$PCA3
u<- mean(y)
std <- sd(y)
# cor(myData$wdefense,myData$PCA3)
std_y <- (y - u)/std
trans_y <- sqrt(std_y+5)
# max(myData[,"wdefense"])
# trans_y = 1/(2.9-myData[,"wdefense"])
# int_3 = myData[,"coded_ms"]*myData[,"self_esteem"]*myData[,"nat_identity"]
# int_2 = myData[,"se2"]*myData[,"coded_ms"]
# idXse = myData[,"se3_ind"]*myData[,"id3_ind"]
# idXms = myData[,"id3_ind"]*myData[,"coded_ms"]
myData = cbind( myData , trans_y)
```

```
yName = "trans_y" ; xName = c("se3_ind","id3_ind","int_111")
fileNameRoot = "study_1_MS_analysis_spread-"
numSavedSteps=20000 ; thinSteps=7
```

Altered code chunk from:
Kruschke, J.K. (2016). Jags-Ymet-XmetMulti-Mrobust.R, Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
model {
   for ( i in 1:Ntotal ) {
     zy[i] ~ dt( sum( zbeta0 + zbeta[1:Nx] * zx[i,1:Nx] ) , 1/zsigma^2 , nu )
   }
   # Priors vague on standardized scale:
   zbeta0 ~ dnorm( 0 , 0.0001 )
   zbeta[1] ~ dnorm(0.5, 50)
   zbeta[2] ~ dnorm(0.5, 50)
   zbeta[3] ~ dnorm(0, 0.0001)
   zsigma ~ dunif( 1.0E-5 , 1.0E+1 )
   nu ~ dexp(1/30.0)
   # Transform to original scale:
   beta[1:Nx] <- ( zbeta[1:Nx] / xsd[1:Nx] )*ysd
   beta0 <- zbeta0*ysd  + ym - sum( zbeta[1:Nx] * xm[1:Nx] / xsd[1:Nx] )*ysd
   sigma <- zsigma*ysd
  }
```

B.6: Model selection code for frequentist methods

from MASS package:

```
library(MASS)
stepReg=MASS::stepAIC(complex_model, direction="both") # also “forward” and “backward”
stepReg$anova
```

from leaps package:

```
all_poss_model <-leaps::regsubsets(y~factor(x1)+factor(x2)+factor(x3)+factor(x4)+factor(x5)+
                                   factor(x6)+factor(x7)+factor(x8)+factor(x9)+factor(x10)+
                                   factor(x11)+factor(x12)+factor(x13)+factor(x14)+factor(x15),
                                 data=msd)
summary(all_poss_model)
plot(all_poss_model, scale="bic", main="Model Selection: mca12 variables assumed metric")
# scale =c("bic", "Cp","adjr2","r2")
```

B.7: Example of model selection code for Bayesian models

Delta variable application taken from:
Kruschke, J.K. (2016). Jags-Ymet-XmetMulti-MrobustVarSelect.R, Jags-Ymet-XmetMulti-MrobustVarSelect-Example.R, Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

Example using delta variable in Ordinal-Probit model selection:

Altered code chunk from:

Kruschke, J.K. (2016). Jags-Yord-XmetMulti-Mnormal.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
model {
    for ( i in 1:Ntotal ) {
      y[i] ~ dcat( pr[i,1:nYlevels] )
      pr[i,1] <- pnorm( thresh[1] , mu[i] , 1/sigma^2 )
      for ( k in 2:(nYlevels-1) ) {
        pr[i,k] <- max( 0 ,  pnorm( thresh[ k ] , mu[i] , 1/sigma^2 )
                         - pnorm( thresh[k-1] , mu[i] , 1/sigma^2 ) )
      }
      pr[i,nYlevels] <- 1 - pnorm( thresh[nYlevels-1] , mu[i] , 1/sigma^2 )
      mu[i] <- zbeta0 + sum( delta[1:Nx]*zbeta[1:Nx] * zx[i,1:Nx] )
    }
    # Priors vague on standardized scale:
      zbeta0 ~ dnorm( (1+nYlevels)/2 , 1/(nYlevels)^2 )
    # zbeta[1] ~ dnorm(-1.5, 50)
    # zbeta[2] ~ dnorm(-1.5, 50)
    # zbeta[3] ~ dnorm(0, 1/(nYlevels)^2)
    for ( j in 1:Nx ) {
      zbeta[j] ~ dnorm( 0 , 1/(nYlevels)^2 )
      # delta[j] ~ dbern( 0.5 )
    }
    zsigma ~ dunif( nYlevels/1000 , nYlevels*10 )
    # Transform to original scale:
    beta[1:Nx] <- (delta[1:Nx]* zbeta[1:Nx] / xsd[1:Nx] )
    beta0 <- zbeta0  - sum( delta[1:Nx]*zbeta[1:Nx] * xm[1:Nx] / xsd[1:Nx] )
    sigma <- zsigma
    for ( k in 2:(nYlevels-2) ) {  # 1 and nYlevels-1 are fixed
      thresh[k] ~ dnorm( k+0.5 , 1/2^2 )
    }
  }
# RUN THE CHAINS
  parameters = c( "beta0" ,  "beta" ,  "sigma", "thresh" , "delta",
                  "zbeta0" , "zbeta" , "zsigma" )
y = data[,yName]
  x = as.matrix(data[,xName])
  mcmcMat = as.matrix(codaSamples,chains=TRUE)
  chainLength = NROW( mcmcMat )
  zbeta0 = mcmcMat[,"zbeta0"]
  zbeta  = mcmcMat[,grep("^zbeta$|^zbeta\\[",colnames(mcmcMat))]
  if ( ncol(x)==1 ) { zbeta = matrix( zbeta , ncol=1 ) }
  zsigma = mcmcMat[,"zsigma"]
  beta0 = mcmcMat[,"beta0"]
  beta  = mcmcMat[,grep("^beta$|^beta\\[",colnames(mcmcMat))]
  if ( ncol(x)==1 ) { beta = matrix( beta , ncol=1 ) }
  thresh  = mcmcMat[,grep("^thresh",colnames(mcmcMat))]
  delta  = mcmcMat[,grep("^delta\\[",colnames(mcmcMat))]
  sigma = mcmcMat[,"sigma"]
#    ADDITIONAL CODE FOR MODEL SELECTION USING DELTA VARIABLE (added to Jags-Yord-XmetMulti-Mnormal.R)
 # Show results for each subset of predictors:
    # This is inelegant code, intended only for a basic illustration.
```

```
  # Recall that delta[j] is inclusion coefficient for predictor j.
#   parameterNames = colnames(mcmcMat)
# deltaCol = grep("delta\\[",parameterNames)
# Npred = length(deltaCol)
# # Show overall inclusion probabilities of each predictor:
# cat("Inclusion probability of each predictor:\n")
# show( xName )
# show( colMeans(mcmcMat[,deltaCol]) )
# # Function to make binary vector of non-neg integer:
# binVecOfI = function( i ) {
#   if ( i ) { c( i %% 2 , binVecOfI( i %/% 2 ) ) } else { NULL }
# }
# # Awkward construction of all possible subsets of predictors:
# for ( modelIdx in 1:(2^Npred) ) {
#   includePred = rep(0,Npred)
#   binVec = binVecOfI(modelIdx-1)
#   if ( length(binVec) ) {
#     for(j in 1:length(binVec) ) { includePred[j]=binVec[j] }
#   }
#   # Extract rows of mcmcMat with this combination of included predictors:
#   cat("  Checking model ",modelIdx," of ",2^Npred," (",includePred,") ...\n")
#   includeSteps = apply( mcmcMat[,deltaCol] , 1 ,
#                         function(m){ (all(m==includePred)) } )
#   if ( sum(includeSteps)>50 ) { # make graph if enough steps
#     includeMat = mcmcMat[includeSteps,]
#     modelProb = nrow(includeMat)/nrow(mcmcMat)
#     Ncol = min(Npred+2,6)
#     Nrow = 1+(Npred)%/%Ncol
#     openGraph(width=Ncol*2.25,height=Nrow*2.0)
#     layout( matrix( 1:(Ncol*Nrow) , ncol=Ncol , nrow=Nrow , byrow=TRUE ) )
#     xLim = range(mcmcMat[,"beta0"])
#     plotPost( includeMat[,"beta0"] , xlab="Intercept" , xlim=xLim ,
#               cenTend="median" , cex.main=2 , border="skyblue" ,
#               main=bquote("Model Prob"==.(round(modelProb,3))))
#     for ( j in 1:Npred ) {
#       parName = paste0("beta[",j,"]")
#       if ( includePred[j] ) {
#         xLim = range(mcmcMat[,parName])
#         plotPost( includeMat[,parName] , cenTend="median" , border="skyblue" ,
#                   xlab=parName , xlim=xLim , main=xName[j] )
#       } else {
#         plot( x=-99,y=-99,xlab="",ylab="",xlim=c(-1,1),ylim=c(-1,1),
#               bty="n",axes=FALSE)
#         text( 0,0,adj=c(0.5,0.5),labels=bquote(delta[.(j)]==0), cex=1.5)
#       }
#     }
#     plotPost( Rsq[includeSteps] , xlab=bquote(R^2) ,
#               main="Prop Var Accntd" ,
#               cenTend="median" , border="skyblue" )
#     saveGraph( file=paste0(saveName,paste0(includePred,collapse="")) ,
#                type=saveType )
#   }
```

```
  # }
```

B.8: Bayesian models for gamma distribution (wdefense trans variable)

Kruschke, J.K. (2016). DBDA2E-utilities.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

Kruschke, J.K. (2016). Jags-Ymet-XmetMulti-Mrobust-Example.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

Altered code chunks from:
Kruschke, J.K. (2016). Jags-Ymet-XmetMulti-Mrobust.R, Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
model {
    # Priors:
    beta0 ~ dnorm(0, 0.0001) # mean, precision = N(0, 10^4)
    beta[1] ~ dnorm(1.5, 50) # se
    beta[2] ~ dnorm(-1.5, 50) # id
    beta[3] ~ dnorm(0, 0.0001) # int
    # beta[4] ~ dnorm(-2, 50)# ms
    # beta[5] ~ dnorm(0, 0.0001)# seXms
    # beta[6] ~ dnorm(0, 0.0001)# idXms
    # beta[7] ~ dnorm(0, 0.0001)# idXse
    shape ~ dunif(0, 200)
    # Likelihood data model:
    for (i in 1:Ntotal) {
      linear_predictor[i] <- sum( beta[]*x[i,])
    y[i] ~ dgamma(shape, shape / exp(beta0+linear_predictor[i]))
  }
}
```

B.9: Bayesian ordinal-probit model in table 7

Altered code chunk from:
Kruschke, J.K. (2016). Jags-Yord-XmetMulti-Mnormal.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
model {
    for ( i in 1:Ntotal ) {
      y[i] ~ dcat( pr[i,1:nYlevels] )
      pr[i,1] <- pnorm( thresh[1] , mu[i] , 1/sigma^2 )
      for ( k in 2:(nYlevels-1) ) {
        pr[i,k] <- max( 0 ,  pnorm( thresh[ k ] , mu[i] , 1/sigma^2 )
                       - pnorm( thresh[k-1] , mu[i] , 1/sigma^2 ) )
      }
      pr[i,nYlevels] <- 1 - pnorm( thresh[nYlevels-1] , mu[i] , 1/sigma^2 )
      mu[i] <- zbeta0 + sum( zbeta[1:Nx] * zx[i,1:Nx] )
    }
    # Priors vague on standardized scale:
      zbeta0 ~ dnorm( (1+nYlevels)/2 , 1/(nYlevels)^2 )
    # zbeta[1] ~ dnorm(-1.5, 50)
    # zbeta[2] ~ dnorm(-1.5, 50)
```

```
    # zbeta[3] ~ dnorm(0, 1/(nYlevels)^2)
    for ( j in 1:Nx ) {
      zbeta[j] ~ dnorm( 0 , 1/(nYlevels)^2 )
    }
    zsigma ~ dunif( nYlevels/1000 , nYlevels*10 )
    # Transform to original scale:
    beta[1:Nx] <- (delta[1:Nx]* zbeta[1:Nx] / xsd[1:Nx] )
    beta0 <- zbeta0  - sum( zbeta[1:Nx] * xm[1:Nx] / xsd[1:Nx] )
    sigma <- zsigma
    for ( k in 2:(nYlevels-2) ) {  # 1 and nYlevels-1 are fixed
      thresh[k] ~ dnorm( k+0.5 , 1/2^2 )
    }
  }
```

Altered code chunk from:
Kruschke, J.K. (2016). Jags-Yord-XmetMulti-Mnormal-Example.R. Received from https://sites.google.com/site/doingbayesiandataanalysis/software-installation

```
myData = read.csv( file="study_1_MS_analysis_spread.csv" )
# int_3 = myData[,"coded_ms"]*myData[,"se3_ind"]*myData[,"id3_ind"]
 # int_2 = myData[,"coded_ms"]*myData[,"se2_ind"]
# int_1 = myData[,"coded_ms"]*myData[,"id3_ind"]
# int_0 = myData[,"se2_ind"]*myData[,"id3_ind"]
 # myData = cbind( myData , int_2, int_1, int_0)
yName = "mca12" ; xName = c("id3_ind", "pair_hse_ms")
                        #
"se1_ind","se2_ind","se3_ind","se4_ind","se5_ind","se6_ind","se7_ind","se8_ind",
                        # "se9_ind","se10_ind","id1_ind","id2_ind","id3_ind","coded_ms", "int_2","int_1")
fileNameRoot = "thesis_1-ordinal-"
numSavedSteps=15000 ; thinSteps=25 # increase for higher ESS
lmInfo <- lm( myData[,yName] ~ myData[,xName[1]]+myData[,xName[2]],
data=myData)#+myData[,xName[3]]+myData[,xName[4]], data=myData)
            # myData[,xName[5]], data=myData)
#+myData[,xName[6]]+myData[,xName[7]]+myData[,xName[8]]+
            # myData[,xName[9]]+myData[,xName[10]]+ myData[,xName[11]]+
            #
myData[,xName[12]]+myData[,xName[13]]+myData[,xName[14]]+myData[,xName[15]]+myData[,
xName[16]], data=myData )
```

B.10: Manual AIC calculation

```
AICmanual <-nrow(msd)*(log(2*pi) + 1 +
log((sum(factor14$residuals^2)/nrow(msd))))+((length(factor14$coefficients)+1)*2)
```

B.11: ordPens regression model

```
setwd("~/Minor_Thesis/terror_management")
msd <- read.csv("ordPens_indicator_variables.csv")
install.packages("ordPens")
library(ordPens)
```

```
# Using all individual questions as factors.
x1 <- msd$se1
x2 <- msd$se2
x3 <- msd$se3
x4 <- msd$se4
x5 <- msd$se5
x6 <- msd$se6
x7 <- msd$se7
x8 <- msd$se8
x9 <- msd$se9
x10 <- msd$se10
x11 <- msd$ident1
x12 <- msd$ident2
x13 <- msd$ident3
x14 <-(msd$se2_ind*msd$coded_ms)+1
x15 <- (msd$id3_ind*msd$coded_ms)+1
x16 <- msd$int_111+1

u <- x16
u <- matrix(u)
x <- cbind(x1,x3,x4,x5,x6,x7,x8,x9,x10,x11,x13)

# transform y (normal)
y<-msd$PCA3 #mca12
uy <- mean(y)
sdy <-sd(y)
std_y <- (y-uy)/sdy
trans_y <- sqrt(std_y+5)
# ANOVA to test x matrix:
ordAOV(x=x, y=y, type = "RLRT", nsim=1000000)
x_aov <- cbind(x3,x13)
lambda <- c(400, 300, 200, 100, 60)
model<- ordSmooth(x=x_aov, y=trans_y, u=u, lambda=lambda)

# ordPens results:
round(model$coefficients,digits=3)
plot(model)
class(model$fitted)
```

B.12: Residual analysis for ordPens model

```
residuals <-as.vector(y - model$fitted)
plot(residuals, type='o',main="Residuals for ordPens Model")
abline(h=0, col='red')
class(residuals)
ur <- mean(residuals)
sdr <- sd(residuals)
std_r <-(residuals - ur)/sdr
shapiro.test(std_r)
plot(density(std_r))
plot(model$fitted~y, main="Residuals vs. Independent Variable")
```

```
plot(std_r ~ model$fitted, main="ordSmooth Model: Residuals vs. Fitted Values",
    ylab="Standardized Residuals", xlab="Fitted Values")#
abline(h=0, col="red")
qqnorm(residuals)
qqline(residuals)
AICmanual <-
nrow(msd)*(log(2*pi)+1+log((sum(residuals^2)/nrow(msd))))+((length(model$coefficients)+1)*2)
AICmanual
```