Ordinal Logistic Regression to Determine Predictors of Stigma Against People with Substance Use Disorders

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The opioid epidemic is an ongoing public health crisis in the United States. While there is continued effort to stop the epidemic through measures such as increasing access to naloxone, a medication designed to rapidly reverse opioid overdoses, and implementing treatment referral protocols, there is concern that stigma against people with Substance Use Disorders (SUD), particularly in people on the front lines of the epidemic, is an obstacle to progress. Previous studies show that first responders do have stigma against people with SUD which influences their perceptions of naloxone and substance use treatments and their interaction with people with SUD. This thesis analyzes responses from Pennsylvania's First Responder Addiction and Connection to Treatment (FR-ACT) program pre-training survey to determine statistically significant predictors for stigma against people with SUD. Specifically, this study looked at three Likert-type questions that were designed to gauge stigma against people with SUD by asking about related topics: connection to treatment, continued drug use, and naloxone use. This is significant to public health because increased understanding of stigma related to SUD can be used to tailor training programs for first responders, and others on the front lines of the epidemic, to reduce stigma and improve the effectiveness of the response to the opioid epidemic. To determine statistically significant predictors for stigma, ordinal logistic regression models were fit for each question. Ordinal logistic regression allowed the natural ordering of the outcome variable, which indicated stigma, to be maintained. The final models were compared to determine if there were consistent predictors for

stigma. The results showed that gender was the only consistent predictor for stigma, with males having more stigma than non-males. Other statistically significant predictors varied depending on the topic being addressed, including organization, experience level, education level, number of overdoses responded to, and region. This suggests that training sessions aimed to reduce stigma and improve responses to opioid overdoses should adjust tactics based on the audience and stigma related topic they intend to cover. The results also suggest that addressing job related burnout and compassion fatigue may help reduce stigma.

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1.0 Introduction

1.1 Background on Opioid Overdose Epidemic and Stigma

Drug overdoses are a serious and persistent public health issue in the United States. Since 2000, there has been a steady increase in overdose deaths, and overdose deaths specifically due to opioids (National Institute on Drug Abuse, 2023). In 2021, overdose deaths significantly increased for all age groups over age 25 from the prior year, with a 22% increase in fatal overdoses caused by synthetic opioids (not including methadone) (Spencer et al., 2022). To combat the opioid overdose epidemic, all states, as of 2023, have enacted laws that allow naloxone access in some form (Legislative Analysis and Public Analysis Association (LAPAA), 2023) and many hospitals have established protocols for referral to treatment (Barnes & McClughen, 2018). Naloxone, also known as Narcan, is "…a life-saving medication that can reverse an overdose from opioids— including heroin, fentanyl, and prescription opioid medications," according to the Centers for Disease Control and Prevention (CDC) (CDC, 2023).

In Pennsylvania, PA Act 139, which went into effect in 2014, gives first responders, including EMS, paramedics, fire fighters and law enforcement, the right to carry and use naloxone to treat those who they believe are having an overdose (Jacoby et al., 2020; The Network, 2015). Currently, it is common for first responders to carry naloxone. In a survey of Pennsylvania police during the years following the introduction of Act 139, approximately 90% of respondents had access to naloxone (Jacoby et al., 2020). Pennsylvania laws also allow "laypersons" to treat presumed overdoses using naloxone with immunity (LAPAA, 2023). As such, access to naloxone has been increasing. The Pennsylvania Commission on Crime and Delinquency (PCCD) sponsors

programs to provide free naloxone to individuals and organizations across the state, including justice system professionals and human services professionals (PCCD, n.d.).

In addition to immediate life saving measures, referral to treatment after an overdose is critical for recovery. First responders are a key link in this process, as they can begin a "warm handoff." A warm handoff is a "seamless transition for opioid overdose survivors from emergency medical care to specialty substance use disorder (SUD) treatment, thus improving the prospect of recovery" (Warm Handoff, n.d.). In Pennsylvania, emergency departments have implemented warm handoff protocols in partnership with the Single County Authorities, local organizations that manage drug and alcohol services, to connect people who are suspected of having SUD to treatment options (Barnes & McClughen, 2018).

There is concern that stigma against people with Substance Use Disorders (SUD) may reduce naloxone use and referral to treatment. Stigma is defined as a practice where groups of people are negatively stereotyped, and identified with distinct language, based on certain characteristics resulting in prejudiced or ostracizing behavior stemming from unequal power dynamics in society (Andersen et al., 2022; Tsai et al., 2019). Andersen et al. (2022) noted that "…groups, not individuals, are the target of stigma, though it is individuals who may be the victims of it." For people with SUD, stigma from people in the healthcare industry and first responders can be especially harmful and lead to poor quality of care, including reduced use of naloxone (Tsai et al., 2019). Additionally, according to Tsai et al. (2019), people with SUD may self-stigmatize because of societal stigma, which is "…associated with psychological distress and poorer quality of life, continued substance use, and reduced engagement with substance use treatment." Therefore, reducing stigma against people with SUD, especially stigma held by first responders, is a key element in solving the opioid overdose epidemic.

Indeed, many studies have shown that some first responders hold negative views of people with SUD, naloxone, and substance use treatment. One survey of police officers found that compassion fatigue, or decreased empathy due to burnout, impacts officers' perceptions and that officers that had responded to an overdose more recently had more negative perceptions of overdose prevention strategies (Carroll et al., 2020). A study of police officers and EMT in Northeastern United States showed they held generally negative views on naloxone administration, including the belief that naloxone promoted continued drug use (Kruis et al., 2022). Another study found that officers felt little compassion for people using illegal drugs (compared to prescription drugs) and felt powerless to help people with SUD, seeing arrest as the most viable option (Green et al., 2013). Another study found that members of law enforcement and EMS had negative views of medication for substance use treatment, including methadone and buprenorphine maintenance therapies (Kruis et al., 2021). These studies show evidence of stigma in first responders and possibly indicate that stigma may make first responders less likely to administer naloxone or refer people with SUD to treatment.

1.2 First Responder Addiction and Connection to Treatment Training Program

The data analyzed in this study was part of the First Responder Addiction and Connection to Treatment (FR-ACT) training program in Pennsylvania. The training program began in 2020 and is still ongoing, with training sessions administered by St. Joseph's University and data evaluated by the University of Pittsburgh. The goal of this program in the short term is to educate first responders on addiction as a disease and use of naloxone and to reduce stigma against people with SUD. In the long term, the goal is to increase naloxone administration, improve responses to

overdoses, and decrease fatal opioid overdoses (University of Pittsburgh, 2020). Originally this program was intended for first responders but has been expanded to include others who interact with people with SUD professionally, including those who work in the legal system and in children and youth services. This program is part of the larger Overdose Data to Action (OD2A) program which is funded by the CDC and gives funds directly to health departments to collect data and implement interventions to address the overdose epidemic (CDC, 2021).

As part of the FR-ACT program, each participant attends one training session and is sent a survey via Qualtrics before and after the session. The survey contains multiple choice questions intended to assess the respondents' knowledge about addiction and naloxone and questions intended to assess the respondents' perceptions and possible stigma about SUD and naloxone. It also includes free response questions regarding the training program. In addition, the survey gathers demographic information about the participants. In this study, only the stigma related pre-training data were analyzed.

1.3 Goal of the Study

The goal of this study was to determine which demographic factors are predictors of stigma against people with SUD, as indicated by level of agreement with a stigma related statement. Specifically, the study looked at stigma in people on the frontline of the opioid epidemic who participated in the FR-ACT training. This study used only the pre-training survey data. Determining if occupation (referred to in this study as organization, e.g. working in a particular sector or in a particular job function, such as law enforcement) is associated with stigma was of foremost interest. Also of interest was whether the association of occupation with stigma differed

across any demographic factors (e.g. an interaction). A final goal was to determine if demographic factors that were statistically significant predictors of stigmatized perceptions relating to SUD were consistent or differed across questions.

Seven stigma related statements were presented in the original survey but only three were evaluated in this study. The survey asked the respondent to indicate their level of agreement with the statement on a 7-level Likert-type scale from "strongly disagree" to "strongly agree", where strongly agreeing would indicate the least amount of stigma. The three statements cover different areas of possible stigma: connection to treatment, continued use of opioids, and access to naloxone. The three stigma statements evaluated in this study are shown in Table 1.

Table 1 Stigma related statements evalued in this study

Statement Number	Statement
1	As a public safety professional, I have an opportunity to assist my community by connecting people to treatment for Substance Use Disorders
2	The continued use of heroin despite the risks of overdose is an indication of a Substance Use Disorder, not a wish to die
3	Leaving naloxone behind with overdose survivors, friends, and/or family members is the right thing to do

1.4 Determining Appropriate Analysis

In this survey, the responses to the stigma-related questions, indicating level of agreement, were Likert-type answers. Likert-type questions are typically used to gauge feelings towards a topic. Often, they are presented as a set of questions pertaining to the same topic, as they were in this survey. When taken together, a set of Likert-type questions can be combined and viewed as a scale, known as a Likert-scale (Batterton & Hale, 2017).

These Likert-type responses are a type of categorical data known as ordinal data which means there are more than two levels of the variable and the levels have a meaningful order but the distance between the levels is not clearly defined (Agresti, 2012). As there is a clear order to Likert-type response levels and there is not a numerically measurable distance between them, Likert-type responses are ordinal data (Batterton & Hale, 2017).

Despite the abundance of Likert-type questions in surveys, there is not a clear consensus on how to analyze the results of them. In general, Likert-type data are either treated as continuous or treated as ordinal. If the Likert-type questions are presented as a set, and intended to be used as a set, then one option is to assign scores to each response level and sum the scores for each respondent resulting in continuous data (Stratton, 2018). There is debate on how to analyze these data, although it is generally concluded that nonparametric methods and statistics, such as medians, are more appropriate than parametric methods and statistics, such as means (Stratton, 2018).

If a Likert-type question is analyzed individually, there is still debate on whether it should be analyzed as ordinal or continuous. Some papers have suggested that so long as there are at least 5 levels in the Likert outcome the data can be analyzed as continuous (Harpe, 2015). Others disagree, stating that analyzing categorical data as continuous data gives invalid and misleading results. Therefore, another option is to analyze Likert outcome data with nominal regression models; however, this ignores the inherent ordering of the Likert outcomes, also leading to incorrect results (Bürkner & Vuorre, 2019). Finally, another option is to use ordinal regression models. These models are the most appropriate but are often not used because they are less known and are perceived as difficult to interpret (Bürkner & Vuorre, 2019). Another concern with ordinal regression models is that the main assumption, the proportional odds assumption, is often violated. However, Harrell (2015) states that the "…proportional hazards assumption is frequently violated,

just as the assumptions of normality of residuals with equal variance in ordinary regression are frequently violated, but the [proportional odds] model can still be useful and powerful in this situation."

In this analysis, I was interested in determining which demographic factors were predictive for agreeing or disagreeing with pre-training stigma-related questions and whether the factors were consistent or differed between different questions. In this case, I was interested in looking at differences between the responses to certain Likert-type questions instead of analyzing the set of questions in the survey together, therefore, using ordinal regression for each question was most appropriate method of analysis.

2.0 Methods

2.1 Data Preparation

The FR-ACT pre-survey data contained responses from March 30th, 2021 to January 5th, 2023, when it was retrieved from Qualtrics. Respondents who indicated they were child welfare professionals or members of children and youth services were excluded from the dataset, as they were administered a unique set of questions in the survey.

The resulting data consisted of 1,550 unique observations. 44 respondents did not answer any of the Likert-type stigma questions, so these observations were excluded, resulting in a dataset with 1,506 observations. Covariates of interest were the participants' gender, age, race, professional organization, education level, years of experience in their organization, number of overdose calls responded to, and region in which the participant worked. Region was not directly asked in the survey and was determined by mapping the self-reported zip code of the participant's work location to its corresponding county and then matching the county to one of six pre-determined Pennsylvania regions: Southeast, Northeast, Southcentral, Northcentral, Southwest, or Northwest (Figure 1).
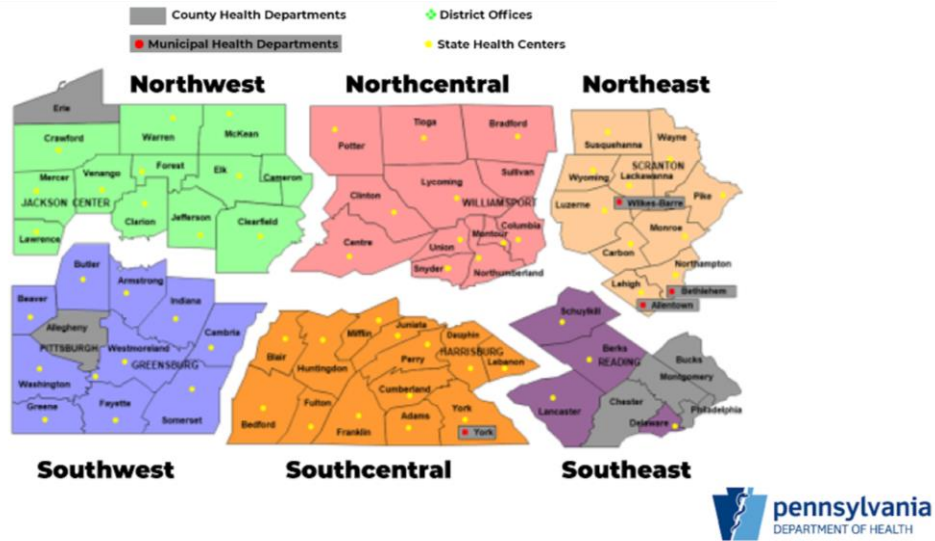
(Reid, 2020)

Figure 1 The six regions of Pennsylvania defined by the Pennsylviania Department of Health

Missingness was checked for all covariates of interest. Of these, all observations had complete data except for the questions regarding overdose responses and region. There were 95 (6%) missing responses for the question regarding zip code and 68 (5%) missing responses for the question asking how many overdose calls the participant had responded to. Missingness indicator variables were created for region and overdose.

As shown in Appendix Table 13, the survey questions for the covariates listed above were presented as multiple-choice with many options to choose from, such as nine choices for race/ethnicity, which resulted in small sample sizes in some of the levels for most of the covariates. For this reason, and for ease of interpretation, every covariate was recategorized (Appendix Table 14).

Gender was binarized in to male or other. Age was binarized into 18-40 or over 40 years of age. Race was binarized into white/Caucasian or other. Number of overdose calls responded to

was binarized into never responded or responded to at least one call. Region was binarized into Southeast Pennsylvania or other Pennsylvania.

Organization, the main covariate of interest, was recategorized into four categories: law enforcement, fire department or EMS, legal related (including lawyers, corrections officers, and judges), and other. Education level was recategorized into three levels: less than a college degree, an associate or bachelor's degree, and a graduate degree. Finally, years of experience in their organization was recategorized into three levels: less than one year, one to ten years, and more than ten years.

The stigma-related questions, which were the outcome of interest, were originally presented as seven level Likert-type questions, ranging from "strongly disagree" to "strongly agree". For each question, the majority of the responses fell into one of the "agree" levels, resulting in small sample sizes in the three "disagree" levels. To ensure that each level had a reasonable sample size for analysis, and for ease of interpretation, the seven level Likert-type options were collapsed into 4 levels: strongly agree, agree, somewhat agree, and neutral/disagree. The three "agree" levels were unaltered while the three "disagree" levels and the "neither agree nor disagree" were combined into a fourth level. This resulted in each level containing at least approximately ten percent of the responses. The original levels and proportions of responses for the stigma questions can be seen in the appendix in Appendix Table 15.

<center>**2.2 Statistical Analysis**</center>

2.2.1 Covariates

Correlation between the covariates was checked pair-wise using the chi-squared test for independence. The chi-squared test for independence tests if two categorical variables are associated, with the null hypothesis being that they are not associated with each other (Carlson, 2021). The tests indicated that many of the covariates were strongly correlated with each other (p-value < 0.001).

The chi-square test for independence was also used to test the correlation between the outcome and each covariate for each question. This was used to get a preliminary sense of which covariates could be predictive in the models.

Here, age was excluded from the analysis. Age was highly correlated with multiple of the other variables, including education and experience. Logically, falling in certain age groups would preclude membership in certain education levels or experience levels. For example, if the participant was less than 20 years old, they would be unable to have more than 10 years of experience or a graduate degree. Age was also less correlated with the outcome than education or experience for each question. Therefore, including age in the models was unnecessary and could have led to confounding.

2.2.2 Ordinal Regression

One form of an ordinal model is the ordinal logistic model. According Agresti (2012), cumulative logits, or log odds, for the model can be written as

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$$\log \frac{P(Y \leq j|x)}{1 - P(Y \leq j|x)} = \log \frac{P(Y \leq j|x)}{P(Y > j|x)} = \text{logit}[P(Y \leq j|x)], \quad j = 1, \dots, J.$$

In this equation, Y is the outcome, x is a covariate and j is a level of the outcome. Within each cumulative logit, the probability (p) of all J levels of the outcome is incorporated (Agresti, 2012).

$$\text{logit}[P(Y \leq j|x)] = \log \frac{p_1(x) + \cdots + p_j(x)}{p_{j+1}(x) + \cdots + p_J(x)}, \quad j = 1, \dots, J.$$

For an ordinal model, a single model is fit where each *J-1* logits has a corresponding intercept but the coefficients for the predictors are constant and shared. For a model with p predictors, this is written as

$$\text{logit}[P(Y \leq j|x)] = \alpha_j + \beta_1 x_1 + \cdots + \beta_p x_p, \quad j = 1, \dots, J$$

where α_j are a set of intercepts (Agresti, 2012).

2.2.2.1 Model Selection

For each of the three stigma-related questions, univariate ordinal logistic regression models were fit for each covariate. Based on the univariate regression results, an initial model containing all of the covariates that were significant at the 0.1 confidence level was constructed for each stigma question. Then, for each question, the significance of each covariate included was tested by comparing the Akaike's information criterion (AIC) for a model with and without the variable. AIC is a measure of prediction error of the model that has a penalty for the number of predictors in the model, where the model with the lower AIC is preferred (Vittinghoff et al., 2012). A change in AIC of 2 or more units was taken to indicate that there was a significant difference between the models (Youk, "Generalized Linear Models", 2022). When testing if a variable was significant by removing it from a model, an AIC that increased by more than 2 units from the previous model indicated that the variable should be kept in the model. If the AIC did not increase by more than 2 units or decreased when the variable was removed, it indicated that the variable was not significant

in the model and the variable was left out. The same logic was used when testing if a variable should be added back into the model.

The significance of the variables in the initial model were tested by individually removing each from the model and comparing AIC. With the exception of organization, which is the main covariate of interest and was kept in the model regardless of significance, covariates that were not significant were removed from the model. When a variable was removed, the change in the coefficients from the previous model was calculated. If any coefficient changed more than 20%, the removed variable was considered a confounder and added back into the model (Ding & Wahed, 2022).

Next, covariates that were removed in earlier stages and covariates that were not included in the initial model due to their univariate significance were added back into the model individually. If the covariate was significant or a confounder it was added back into the model.

Finally, interactions between organization and the other covariates in the model were tested. If the interaction was significant based on AIC, the interaction was included in the final model.

For each final model, collinearity was checked by calculating the variance inflation factor (VIF). VIF is a measure of multicollinearity in the model and reflects the increase in the variance of coefficients in the model due to this (Vittinghoff et al., 2012). VIFs under 10 were considered acceptable, indicating that there were no issues with collinearity reducing the precision of the coefficients in the model (Youk, "Collinearity", 2022).

2.2.2.2 Odds Ratios

Odds ratios are often used to interpret the results of a logistic regression and can also be used for interpreting the results of an ordinal logistic regression. For an ordinal logistic model with

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one a binary covariate, x, the conditional logits can be expressed as shown below (UCLA: Statistical Consulting Group [UCLA SCG], "How do I…?", n.d.).

$$\text{logit}[P(Y \leq j | x = 0)] = \beta_0$$

$$\text{logit}[P(Y \leq j | x = 1)] = \beta_0 + \beta_1 x_1$$

The odds ratio for that covariate can be expressed as shown below (UCLA SCG, "How do I…?", n.d.).

$$\frac{\text{logit}[P(Y \leq j | x = 1)]}{\text{logit}[P(Y \leq j | x = 0)]} = \exp(\beta_1).$$

2.2.2.3 Model Parameterization and Interpretation

Analysis in this study used the package "polr" in R to perform the ordinal logistic regression. It is important to note that the parameterization of ordinal logistic models in this package is counterintuitive. The coefficients (η) output by polr ordinal logistic models are the negative of the coefficients for the model.

$$\eta_i = -\beta_i$$

For this reason, the odds ratios from the model outputs in this study are not interpreted as expected in Section 2.2.2.2 (UCLA SCG, "How do I…?", n.d.).

Therefore, keeping in mind the parameterization of the polr model, the odds ratio obtained is actually computed with the reference category in the numerator (UCLA SCG, "How do I…?", n.d.).

$$\frac{\text{logit}[P(Y \leq j | x = 0)]}{\text{logit}[P(Y \leq j | x = 1)]} = \exp(\eta_1) = \exp(-\beta_1).$$

For example, in this analysis there are 4 levels of the outcome, referred to going forward as stigma, which are coded as 0, 1, 2, and 3. "Strongly agree" is the reference level (0), "agree" is coded as 1, "somewhat agree" is coded as 2, and "neutral/disagree" is coded as 3. A univariate

model of stigma using gender as a predictor, coded with male as the reference category (0) compared to non-male (1) may result in an odds ratio of 0.70. This would be describing the relationship shown below.

$$\frac{\text{logit}[P(Y \leq 0|x = 0)]}{\text{logit}[P(Y \leq 0|x = 1)]} = 0.70.$$

The interpretation would be that for males, the odds of strongly agreeing (versus agreeing, somewhat agreeing, or being neural/disagreeing) with the statement are 30% lower than the odds for those who are not male.

2.2.2.4 Checking Assumptions

There are three main assumptions for ordinal logistic regression. The first assumption is that the outcome is an ordinal variable, which is satisfied in this case. The second assumption is that the predictors are independent of each other. While initial tests indicated that some of the covariates were correlated, there were no collinearity issues in the models so this assumption can be considered satisfied. The final assumption is the proportional odds assumption. (Harrell, 2015)

2.2.2.4.1 Proportional Odds Assumption

The proportional odds assumption allows a single set of coefficients to be used in the ordinal logistic model. This assumption means that the same set of coefficients can describe the odds of strongly agreeing with the statement compared to any other response and the odds of agreeing or strongly agreeing compared to any other response. The relationship is the same for each grouped comparison of the outcome (UCLA SCG, "Ordinal logistic regression", n.d.). That is,

$$Odds\ ratio = \frac{(Y \le 0|x = 0)/(Y > 0|x = 0)}{(Y \le 0|x = 1)/(Y > 0|x = 1)} = \frac{(Y \le 1|x = 0)/(Y > 1|x = 0)}{(Y \le 1|x = 1)/(Y > 1|x = 1)} =$$

$$\frac{(Y \le j|x = 0)/(Y > j|x = 0)}{(Y \le j|x = 1)/(Y > j|x = 1)}, \quad j = 0, \dots, J.$$

If the proportional odds assumption is violated, it suggests that the single set of coefficients is not appropriate to describe the relationship between all the comparisons of the outcome. In other words, the effect of the covariate differs between different levels or pairing of the outcome (UCLA SCG, "Ordinal logistic regression", n.d.).

UCLA Statistical Consulting Group outlines a graphical check for the proportional odds assumption. This involves plotting the differences between the log-odds of being greater than or equal to the levels of the outcome, based on the "predicted values we would get if we regressed our dependent variable on our predictor variables one at a time, without the parallel slopes assumption" (UCLA SCG, "Ordinal logistic regression: Proportional odds assumption", n.d.). This is done for each level of the predictor. If this difference in logits is similar between each level of the predictor, the assumption holds. If it is not similar, it may suggest the proportional odds assumption is violated. This is visually judged from the plot (UCLA SCG, "Ordinal logistic regression", n.d.).

As additional validation for models that appear to violate the proportional odds assumption, I also ran logistic regressions with the same covariates. The outcome was binarized into "agree" or "neutral/disagree" by combining all of the "agree" levels. The same covariates as the final ordinal models were added into the logistic models, regardless of significance. The direction of the odds ratios obtained from the logistic model were used as a crude check for the effects seen in the ordinal logistic models.

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3.0 Results

3.1 Descriptive Statistics

After collapsing the levels for all covariates, every level of a covariate contains at least 10% of the data. Gender, age, race, number of responses to overdose calls, and region were binarized. Organization, education level, and years of experience in organization were made into three or four level categorical variables. Table 2 shows the new levels of the covariates and the counts and percents of the responses for each covariate after they were recategorized.

Table 2 Counts and percents of responses for recategorized covariates

Covariate	Level (Code)	Count (Percent)
Gender	Male (0)	915 (60.8%)
	Other (1)	591 (39.2%)
Age (years)	Under 40 and Prefer Not to Say (0)	755 (50.1%)
	40 and Over (1)	751 (49.9%)
Race/Ethnicity	White and Caucasian (0)	1271 (84.4%)
	Other (1)	235 (15.6%)
Education	Less than college (0)	382 (25.4%)
	Associate or bachelor's degree (1)	802 (53.3%)
	Graduate degree (2)	322 (21.4%)
Organization	Law enforcement (0)	532 (35.3%)
	Fire department and EMS (1)	180 (12.0%)
	Legal (2)	383 (25.4%)
	Other (3)	411 (27.3%)

Table 2 Counts and percents of responses for recategorized covariates continued

Experience in Organization (years)	Less than 1 (0)	281 (18.7%)
	1-10 (1)	491 (32.6%)
	More than 10 (2)	734 (48.7%)
Overdose Calls Responded To (number)	Never responded (0)	983 (65.3%)
	Responded to at least 1 (1)	523 (34.7%)
Region of PA	Other PA (0)	870 (57.8%)
	Southeast (1)	636 (42.2%)

The proportion of responses for the stigma questions with collapsed Likert levels are shown in Table 3.

Table 3 Counts and percents for recategorized four-level Likert scale stigma questions

Ordinal Outcome Levels	Question 1: Connecting to Treatment	Question 2: Continued Use of Heroin	Question 3: Leaving Naloxone Behind
	Count (Percent)		
Strongly Agree (0)	550 (36.5%)	620 (41.2%)	416 (27.6%)
Agree (1)	553 (35.4%)	552 (36.7%)	388 (25.8%)
Somewhat Agree (2)	196 (13.0%)	148 (9.8%)	233 (15.5%)
Neutral or Disagree (3)	227 (15.1%)	186 (12.4%)	469 (31.1%)

3.2 Univariate Analysis

3.2.1 Univariate Analysis for Stigma Question 1

Question 1 asked the participant to indicate their level of agreement with the statement "As a public safety professional, I have an opportunity to assist my community by connecting people to treatment for Substance Use Disorders". At the 0.1 confidence level, organization, gender, age, education level, and years of experience were statistically significant for predicting the stigma outcome for question 1. Missingness for number of responses to overdose calls and missingness for region were not statistically significant in the univariate analysis at the 0.1 confidence level and were not considered in the model going forward.

Table 4 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 1

Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	2.14 [1.57, 2.92]	<0.001
	Legal (2)	0.882 [0.693, 1.12]	0.307
	Other (3)	1.09 [0.863, 1.38]	0.462
Gender: Male (0)	Other (1)	0.767 [0.634, 0.927]	0.00626
Race: White/Caucasian (0)	Other (1)	1.00 [0.776, 1.29]	0.989
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.732 [0.586, 0.913]	0.00571
	Graduate Degree (2)	0.763 [0.582, 1.00]	0.0499
Experience (years): Less than 1 year (0)	1-10 (1)	1.67 [1.28, 2.20]	<0.001
	More than 10 (2)	1.90 [1.48, 2.46]	<0.001
Overdoses (number): None (0)	At least 1 (1)	1.20 [0.988, 1.45]	0.0659
Region: Other PA (0)	Southeast PA (1)	1.16 [0.967, 1.40]	0.109

Table 4 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 1 continued

Overdose Missing: Complete (0)	Missing (1)	1.23 [0.80, 1.91]	0.347
Region Missing: Complete (0)	Missing (1)	0.788 [0.536, 1.15]	0.222

3.2.2 Univariate Analysis for Stigma Question 2

Question 2 asked the participant to indicate their level of agreement with the statement "The continued use of heroin despite the risks of overdose is an indication of a Substance Use Disorder, not a wish to die". At the 0.1 confidence level, organization, gender, education level, and number of responses to overdose calls were statistically significant for predicting the stigma outcome for Question 2. Missingness for number of responses to overdose calls and missingness for region were not statistically significant at the 0.1 confidence level and were not considered in the model going forward.

Table 5 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 2

Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	1.13 [0.834, 1.54]	0.419
	Legal (2)	0.944 [0.743, 1.20]	0.634
	Other (3)	0.607 [0.475, 0.775]	<0.001
Gender: Male (0)	Other (1)	0.671 [0.553, 0.814]	<0.001
Race: White/Caucasian (0)	Other (1)	1.17 [0.905, 1.52]	0.227
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.782 [0.623, 0.980]	0.0327
	Graduate Degree (2)	0.420 [0.316, 0.558]	<0.001

Table 5 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 2 continued

Experience (years): Less than 1 year (0)	1-10 (1)	0.913 [0.697, 1.20]	0.508
	More than 10 (2)	1.07 [0.832, 1.38]	0.595
Overdoses (number): None (0)	At least 1 (1)	1.45 [1.19, 1.77]	<0.001
Region: Other PA (0)	Southeast PA (1)	1.13 [0.939, 1.37]	0.197
Overdose Missing: Complete (0)	Missing (1)	1.13 [0.729, 1.76]	0.573
Region Missing: Complete (0)	Missing (1)	0.929 [0.633, 1.36]	0.703

3.2.3 Univariate Analysis for Stigma Question 3

Question 3 asked the participant to indicate their level of agreement with the statement "Leaving naloxone behind with overdose survivors, friends, and/or family members is the right thing to do". At the 0.1 confidence level, organization, gender, education level, years of experience, and number of responses to overdose calls were all statistically significant for predicting the stigma outcome for Question 3. Missingness for number of responses to overdose calls and missingness for region were not statistically significant at the 0.1 confidence level and were not considered in the model going forward.

Table 6 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 3

Covariate: Reference (code)	Level (code)	Odds Ratios [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	0.907 [0.671, 1.23]	0.523
	Legal (2)	0.583 [0.461, 0.737]	<0.001
	Other (3)	0.367 [0.288, 0.467]	<0.001

Table 6 Univariate ordinal regression odds ratios, 95% confidence intervals, and P-values for Question 3 continued

Gender: Male (0)	Other (1)	0.569 [0.472, 0.687]	<0.001
Race: White/Caucasian (0)	Other (1)	1.21 [0.941, 1.56]	0.138
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.818 [0.654, 1.02]	0.0766
	Graduate Degree (2)	0.425 [0.322, 0.559]	<0.001
Experience (years): Less than 1 year (0)	1-10 (1)	0.602 [0.461, 0.786]	<0.001
	More than 10 (2)	0.677 [0.527, 0.869]	0.00221
Overdoses (number): None (0)	At least 1 (1)	1.30 [1.08, 1.58]	0.00674
Region: Other PA (0)	Southeast PA (1)	0.917 [0.763, 1.10]	0.352
Overdose Missing: Complete (0)	Missing (1)	1.27 [0.818, 1.97]	0.290
Region Missing: Complete (0)	Missing (1)	0.789 [0.544, 1.14]	0.209

3.3 Ordinal Regression

3.3.1 Ordinal Regression for Stigma Question 1

Table 7 shows the final model for Question 1, "As a public safety professional, I have an opportunity to assist my community by connecting people to treatment for Substance Use Disorders". Organization, gender, experience, and overdose were included in the initial model based on the univariate analysis. Overdose was not statistically significant in the model based on AIC but resulted in a greater than 20% change in a coefficient for organization when removed. Therefore, overdose was considered a confounder and included in the model. The three other initial variables were all statistically significant.

When added into the model, region was not statistically significant but was a confounder for organization. Region was added into the model and interaction testing indicated that there was a statistically significant interaction between region and organization. No other interactions were statistically significant.

The odds ratios, confidence intervals, and P-values for the model for Question 1 are shown in the table below.

Table 7 Odds ratios, 95% confidence intervals, and P-values for the final ordinal model for Question 1

Covariate: Reference (code)	Level (code)	Odds Ratios [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	2.92 [1.86, 4.57]	<0.001
	Legal (2)	1.14 [0.790, 1.66]	0.475
	Other (3)	1.39 [0.977, 1.98]	0.0673
Gender: Male (0)	Other (1)	0.788 [0.635, 0.977]	0.0301
Experience (years): Less than 1 year (0)	1-10 (1)	1.52 [1.11, 2.06]	0.00830
	More than 10 (2)	1.62 [1.21, 2.18]	0.0124
Overdoses (number): None (0)	At least 1 (1)	0.873 [0.691, 1.10]	0.256
Region: Other PA (0)	Southeast PA (1)	1.69 [1.21, 2.36]	0.00203
Organization*Region: Law Enforcement (0) * Other PA (0)	Fire/EMS (1) * Southeast PA (1)	0.446 [0.237, 0.840]	0.0125
	Legal (2) * Southeast PA (1)	0.532 [0.318, 0.890]	0.0163
	Other (3) * Southeast PA (1)	0.604 [0.362, 1.01]	0.0531
Intercepts	Strongly Agree | Agree (0 | 1)	0.973	0.839
	Agree | Somewhat Agree (1 | 2)	4.56	<0.001
	Somewhat Agree | Neutral or Disagree (2 | 3)	10.26	<0.001

For those who are male, the odds of strongly agreeing with the statement (versus not, i.e., agreeing, somewhat agreeing or being neutral/disagreeing) is estimated to be 21% lower than for those who are not male, although this could be as much as 36% lower or as little as 2% lower.

For those with less than 1 year of experience in their organization, the odds of strongly agreeing with the statement is estimated to be 1.52 times higher than those with 1 to 10 years of experience, although this could be as little as 1.11 times higher or as much as 2.06 times higher. For those with less than 1 year of experience in their organization, the odds of strongly agreeing with the statement is estimated to be 1.62 times higher than those with more than 10 years of experience, although this could be as little as 1.21 times higher or as much as 2.18 times higher.

For those who have never responded to an overdose call, the odds of strongly agreeing with the statement is estimated to be 13% lower than for those who have responded to at least one overdose call, although this is not a statistically significant result.

As there is a significant interaction between organization and region, these two covariates must be interpreted together.

For those in law enforcement working in non-Southeast Pennsylvania, the odds of strongly agreeing with the statement is estimated to be 2.91 times higher than for those in the fire department or EMS working in non-Southeast Pennsylvania, although it could be a little as 1.86 times higher or as much as 4.57 times higher. For those in law enforcement working in non-Southeast Pennsylvania, the odds of strongly agreeing with the statement is estimated to be 14% higher than for those in a legal related organization working in non-Southeast Pennsylvania, although this is not a statistically significant result. For those in law enforcement working in non-Southeast Pennsylvania, the odds of strongly agreeing with the statement is estimated to be 39%

higher than for those in the "other" organization included in the training working in non-Southeast Pennsylvania, although this is not a statistically significant result.

For those working in non-Southeast Pennsylvania in law enforcement, the odds of strongly agreeing with the statement is estimated to be 1.69 times higher than for those working in Southeast Pennsylvania in law enforcement, although it could be little as 1.21 times higher or as much as 2.36 times higher.

For those working in non-Southeast Pennsylvania in law enforcement, the odds of strongly agreeing with the statement is estimated to be 55% lower than for those working in southeast Pennsylvania in a fire department or EMS, although this could be as much as 76% lower as or as little as 16% lower. For those working in non-Southeast Pennsylvania in law enforcement, the odds of strongly agreeing with the statement is estimated to be 47% lower than for those working in southeast Pennsylvania in a legal related organization, although this could be as much as 68% lower or as little as 11% lower. For those working in non-Southeast Pennsylvania in law enforcement, the odds of strongly agreeing with the statement is estimated to be 40% lower than for those working in southeast Pennsylvania in the "other" organization included in the training, although this is not a statistically significant result.

3.3.2 Ordinal Regression for Stigma Question 2

Table 8 shows the final model for Question 2, "The continued use of heroin despite the risks of overdose is an indication of Substance Use Disorder, not a wish to die". Organization, gender, education, and overdose were included in the initial model based on the univariate analysis. Organization was not statistically significant in the model based on AIC but it is the main predictor of interest so it was kept in the model. The three other initial variables were all statistically

significant. No other covariates were statistically significant or confounding. There were no statistically significant interactions.

The odds ratios, confidence intervals, and P-values for the models for Question 2 are shown in the table below.

Table 8 Odds ratios, 95% confidence intervals, and P-values for the final ordinal model for Question 2

Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	1.05 [0.766, 1.44]	0.765
	Legal (2)	1.19 [0.917, 1.54]	0.191
	Other (3)	0.857 [0.646, 1.14]	0.284
Gender: Male (0)	Other (1)	0.767 [0.619, 0.950]	0.0154
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.821 [0.651, 1.04]	0.0959
	Graduate Degree (2)	0.469 [0.349, 0.629]	<0.001
Overdoses (number): None (0)	At least 1 (1)	1.26 [1.01, 1.57]	0.0389
Intercepts	Strongly Agree | Agree (0 | 1)	0.524	<0.001
	Agree | Somewhat Agree (1 | 2)	2.77	<0.001
	Somewhat Agree | Neutral or Disagree (2 | 3)	5.66	<0.001

For those in law enforcement, the odds of strongly agreeing with the statement (versus not, i.e. agreeing, somewhat agreeing or being neutral/disagreeing) is estimated to be 5% higher than for those in the fire department or EMS, although this is not a statistically significant result. The odds of strongly agreeing with the statement for those in law enforcement is estimated to be 19% higher than for those in organizations related to the legal system, although this is not a statistically significant result. The odds of strongly agreeing with the statement for those in law enforcement

is estimated to be 14% lower than for those in other organizations included in the training, although this is not a statistically significant result.

For males, the odds of strongly agreeing with the statement is estimated to be 23% lower than for non-males, although it could be as much as 38% lower or as little as 5% lower.

The odds of strongly agreeing with the statement for those with no college education is estimated to be 18% lower than for those with an associate or bachelor's degree, although this is not a statistically significant result. The odds of strongly agreeing with the statement for those with no college education is estimated to be 53% lower than for those with a graduate degree, although it could be as much as 65% lower or as little as 37% lower.

For those who never responded to an overdose call, the odds of strongly agreeing with the statement is estimated to be 26% higher than for those who have responded to at least one overdose call, although it could be as much as 57% higher or as little as 1% higher.

3.3.3 Ordinal Regression for Stigma Question 3

Table 9 shows the final model for Question 3, "Leaving naloxone behind with overdose survivors, friends, and/or family members is the right thing to do". Organization, gender, education, experience and overdose were included in the initial model based on the univariate analysis. Overdose was not statistically significant in the model based on AIC and it was not a confounder so it was removed from the model. Experience was also not statistically significant in the model. However, it was a confounder for organization based on a greater than 20% change in a coefficient when experience was removed from the model, so experience was kept in the model. The three other initial variables were all statistically significant. No other covariates were statistically significant or confounding. There were no statistically significant interactions.

The odds ratios for the models for question 3 are shown in the table below.

Table 9 Odds ratios, 95% confidence intervals, and P-values for the final ordinal model for Question 3

Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]	P-value
Organization: Law Enforcement (0)	Fire Department and EMS (1)	0.910 [0.666, 1.24]	0.554
	Legal (2)	0.697 [0.544, 0.893]	0.00428
	Other (3)	0.483 [0.369, 0.632]	<0.001
Gender: Male (0)	Other (1)	0.767 [0.621, 0.947]	0.0135
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.854 [0.679, 1.07]	0.176
	Graduate Degree (2)	0.537 [0.402, 0.715]	<0.001
Experience (years): Less than 1 year (0)	1-10 (1)	0.761 [0.577, 1.00]	0.0527
	More than 10 (2)	0.790 [0.608, 1.03]	0.0766
Intercepts	Strongly Agree | Agree (0 | 1)	0.160	<0.001
	Agree | Somewhat Agree (1 | 2)	0.512	<0.001
	Somewhat Agree | Neutral or Disagree (2 | 3)	1.02	0.897

For those in law enforcement, the odds of strongly agreeing with the statement (versus not, i.e., agreeing, somewhat agreeing or being neutral/disagreeing) is estimated to be 9% lower than for those in the fire department or EMS, although this is not a statistically significant result. The odds of strongly agreeing with the statement for those in law enforcement is estimated to be 30% lower than for those in organizations related to the legal system, although it could be as much as 46% lower or as little as 11% lower. The odds of strongly agreeing with the statement for those in law enforcement is estimated to be 52% lower than for those in other organizations included in the training, although it could be as much as 63% lower or as little as 37% lower.

For males, the odds of strongly agreeing with the statement is estimated to be 23% lower than for non-males, although it could be as much as 38% lower or as little as 5% lower.

The odds of strongly agreeing with the statement for those with no college education is estimated to be 15% lower than for those with an associate or bachelor's degree, although this is not a statistically significant result. The odds of strongly agreeing with the statement for those with no college education is estimated to be 46% lower than for those with a graduate degree, although it could be as much as 60% lower or as little as 28% lower.

The odds of strongly agreeing with the statement for those with less than 1 year of experience in their organization is estimated to be 24% lower than for those with 1 to 10 years of experience, although it could be as much as 42% lower or as little as 0% lower. The odds of strongly agreeing with the statement for those with less than 1 year of experience in their organization is estimated to be 21% lower than for those with more than 10 years of experience, although it is not a statistically significant result.

3.4 Proportional Odds Assumption

The proportional odds assumption is the main assumption for ordinal regression. If the assumption holds, the logit for each level of the covariate would be close in distance to one another. The more distance horizontally between the levels of the covariate, the more of an indication that the assumption is violated.

3.4.1 Proportional Odds Assumption for Stigma Question 1

3.4.1.1 Graphical Method
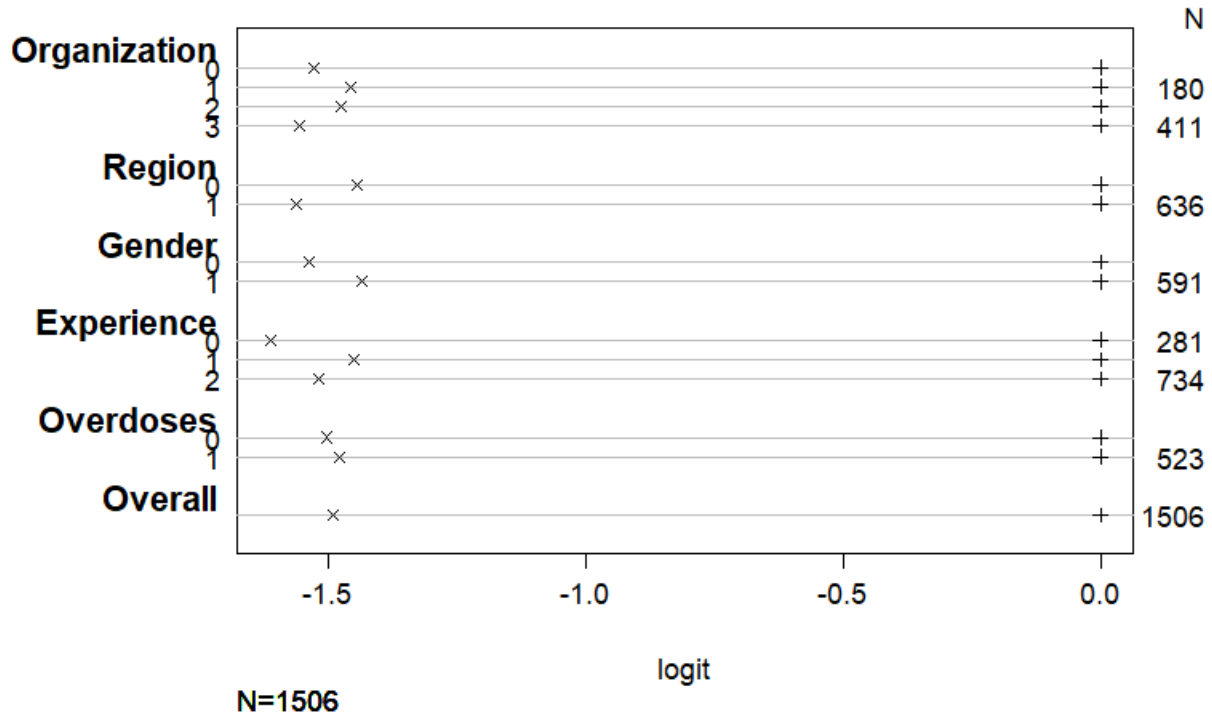
Figure 2 Graphical check of proportional odds sssumption for all covariates in Question 1 model

Figure 2 shows the graphical check of the proportional odds assumption for the Question 1 model. Here, each level of each variable is clustered around logit = -1.5. There does not seem to be any notable spread in the tick marks. Based on the graph, it appears that that the proportional odds assumption holds for this model so no additional assumption testing was done.

3.4.2 Proportional Odds Assumption for Stigma Question 2

3.4.2.1 Graphical Method
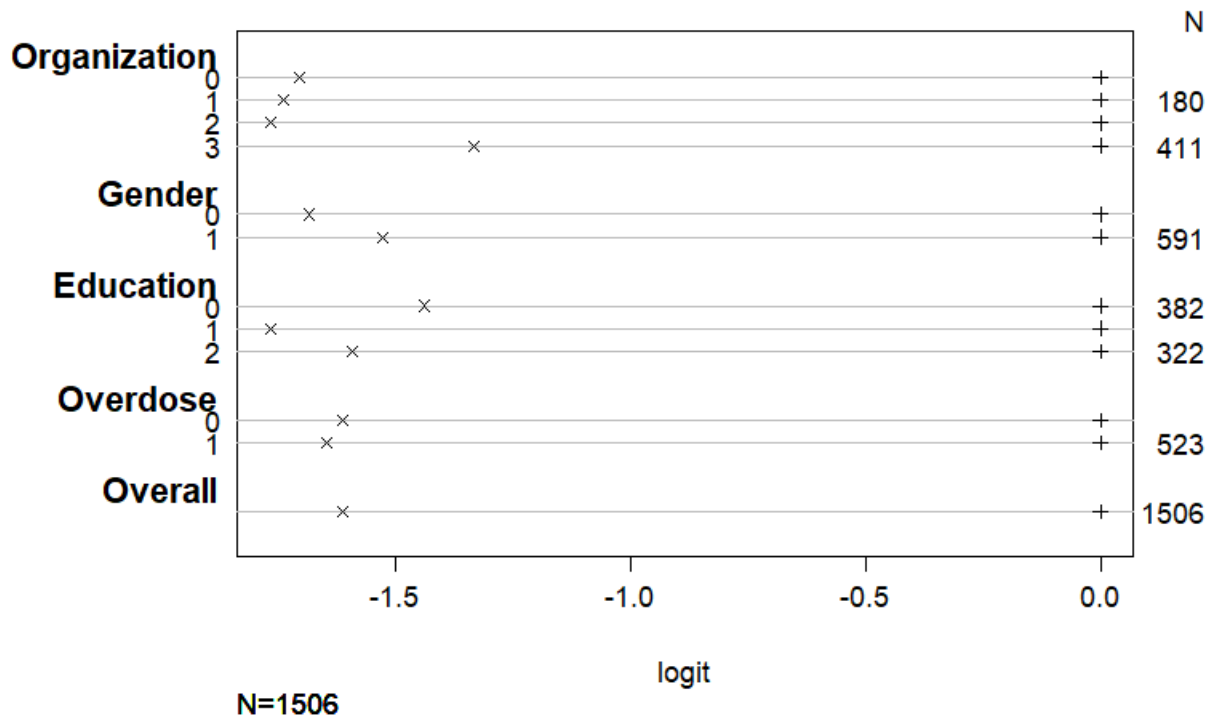
Figure 3 Graphical check of proportional odds sssumption for all covariates in Question 2 model

Figure 3 shows the graphical check of the proportional odds assumption for the Question 2 model. The logits for gender and overdose appear to close to each other within the variable. This indicates that the proportional odds assumption holds for these variables. Logits for levels 0-2 for organization appear to be clustered close together but level 3 is visibly separate from the other levels. There also appears to be some spread for the logits for all three levels of education. This would indicate that there are possibly violations of the proportional odds assumption for organization and education in this model.

The implication of the violation of the proportional odds assumption for organization is that belonging to an organization in the "Other" category versus any of the other organization categories may result in a different effect when going from the different level responses in the stigma question. This effect may have been better described by having a separate set of coefficients to describe the relationship between the outcome levels for those in the "Other" category of organization. The same is true for the levels of education.

3.4.2.2 Logistic Regression for Validation

Logistic regression was used to determine if the violation of the proportional odds assumption in this model had a significant effect on the conclusions from the model. The previously 4-level ordinal outcome was binarized into "agree (0)" and "neutral/disagree (1)." The results of this model are shown in Table 10.

Table 10 Odds ratios and 95% confidence intervals for logisitc regression model for Question 2

Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]
Organization:	Fire Department and EMS (1)	0.925 [0.549, 1.52]
Law Enforcement (0)	Legal (2)	0.984 [0.628, 1.53]
	Other (3)	1.41 [0.899, 2.22]
Gender: Male (0)	Other (1)	0.783 [0.542, 1.12]
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.543 [0.384, 0.771]
	Graduate Degree (2)	0.371 [0.223, 0.599]
Overdoses (number): None (0)	At least 1 (1)	1.18 [0.829, 1.68]

If there are no serious effects on the ordinal model from the violation of the proportional odds assumption, the effect of the covariates on the outcome would likely be similar.

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 8% lower for those who belong to the fire department or EMS compared to those who belong to law enforcement, but it is not a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 2% lower for those who belong to legal organizations compared to those who belong to law enforcement, but it is not a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 41% higher for those in other organizations compared to those who belong to law enforcement, but this is not a significant result. Comparing these results to the results of the ordinal regression for the same question, the direction of the effects do not agree. However, none of the organization results are significant in this model, nor were they significant in the ordinal model so the direction of the effect is not meaningful.

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 22% lower for those who are non-male compared to those who are male, but it is not a significant result. Compared to the ordinal model, the direction of this effect agrees well.

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 46% lower for those with no college education compared to those with an associate or bachelor's degree, and it is a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 63% lower for those with no college education compared to those with graduate degree, and it is a significant result. Compared to the ordinal model, the direction of these effects agrees well.

Finally, for the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 18% higher for those who have responded to at least one overdose call

compared to those who have not responded to any overdose calls, although this is not a significant result. Compared to the ordinal model, the direction of this effect agrees well.

In the cases of gender, education, and overdose response, the logistic model shows some support for the effects seen in the ordinal model. It is still possible that the violation of the proportional odds assumption is distorting the effect of organization and education. This is not a definitive validation because the significance of the covariates is not the same in the two models.

3.4.3 Proportional Odds Assumption for Stigma Question 3

3.4.3.1 Graphical Method
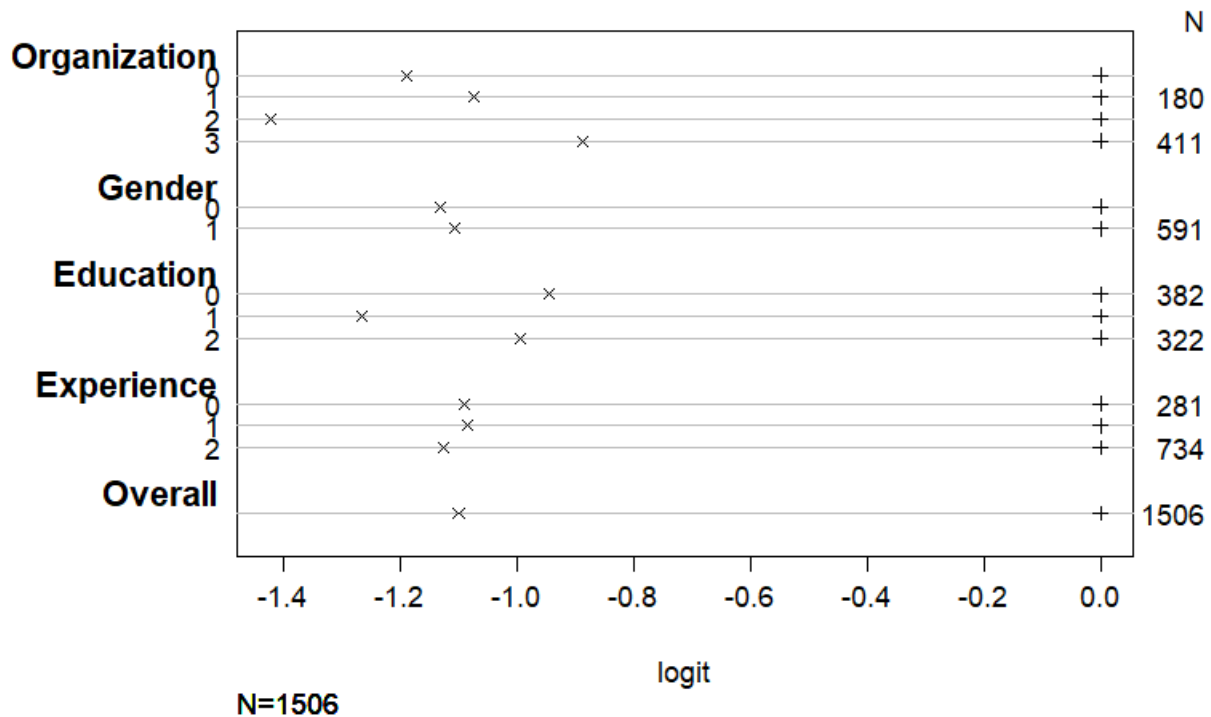
Figure 4 Graphical check of proportional odds sssumption for all covariates in Question 3 model

Figure 4 shows the graphical check of the proportional odds assumption for the Question 3 model. The logits for gender and experience appear to close to each other within the levels of the variable. This indicates that the proportional odds assumption holds for these variables. Logits all levels of organization appear to be spread out from each other. Level 1 of education also appears to be visibly separated from level 0 and 2. This would indicate that there are possibly violations of the proportional odds assumption for organization and education in this model. The implication is similar to that described above for organization and education. The effect of being in a certain organization or having a certain education level may not be constant between different groups of the outcome variable. These effects may be better described by having individual coefficients to describe the effect for each group of levels of the outcome variable.

3.4.3.2 Logistic Regression for Validation

Because the graphical check appeared to show a violation of the proportional odds assumption, logistic regression modeling was done (Table 11).

Table 11 Odds ratios and 95% confidence intervals for logisitc regression model for Question 3

| Covariate: Reference (code)	Level (code)	Odds Ratio [95% CI]
Organization: Law Enforcement (0)	Fire Department and EMS (1)	0.715 [0.491, 1.72]
	Legal (2)	0.581 [0.427, 0.787]
	Other (3)	0.595 [0.430, 0.821]
Gender: Male (0)	Other (1)	0.748 [0.575, 0.971]
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	0.663 [0.510, 0.864]
	Graduate Degree (2)	0.488 [0.342, 0.690]
Experience (years): Less than 1 year (0)	1-10 (1)	0.747 [0.540, 1.03]
	More than 10 (2)	0.737 [0.545, 1.00]

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 28% lower for those who belong to the fire department or EMS compared to those who belong to law enforcement, but it is not a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 42% lower for those who belong to legal organizations compared to those who belong to law enforcement, and this is a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 40% lower for those in other organizations compared to those who belong to law enforcement, and this is a significant result. Comparing this to the results of the ordinal regression for the same question, the direction of the effects agrees well.

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 25% lower for those who are non-male compared to those who are male, and this is a significant result. Compared to the ordinal model, the direction of this effect agrees well.

For the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 34% lower for those with no college education compared to those with an associate or bachelor's degree, and it is a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 51% lower for those with no college education compared to those with graduate degree, and it is a significant result. Compared to the ordinal model, the direction of these effects agrees well.

Finally, for the logistic model, the odds of being neutral or disagreeing with the statement are estimated to be 25% lower for those who have 1 to 10 years of experience compared to those with less than 1 year of experience, although this is not a significant result. The odds of being neutral or disagreeing with the statement are estimated to be 26% lower for those who have 10 or more years of experience compared to those with less than 1 year of experience, although this is

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only a borderline significant result. Compared to the ordinal model, the direction of these effects agrees well.

For all the covariates, the logistic model shows support for the effects seen in the ordinal model. It is still possible that the violation of the proportional odds assumption is distorting the effect of organization and education. This is not a definitive validation because the significance of the covariates is not the same in the two models.

3.5 Summary of Results

The table below (Table 12) shows the results of the three ordinal models together for comparison.

Table 12 Comparison of ordinal logistic model results for all stigma questions.

Covariate: Reference (code)	Level (code)	Odds Ratio (significance)		
		Model 1: Connecting to Treatment	Model 2: Continued Use of Heroin	Model 3: Leaving Naloxone Behind
Organization: Law Enforcement (0)	Fire Department and EMS (1)	2.92 (***)	1.05 (ns)	0.910 (ns)
	Legal (2)	1.14 (ns)	1.19 (ns)	0.697 (**)
	Other (3)	1.39 (ns)	0.857 (ns)	0.483 (***)
Gender: Male (0)	Other (1)	0.788 (*)	0.767 (*)	0.767 (*)
Education: Less than a college degree (0)	Associate or bachelor's degree (1)	NA	0.821 (ns)	0.854 (ns)
	Graduate Degree (2)	NA	0.469 (***)	0.537 (***)

Experience (years): Less than 1 year (0)	1-10 (1)	1.52 (**)	NA	0.761 (ns)
	More than 10 (2)	1.62 (*)	NA	0.790 (ns)
Overdoses (number): None (0)	At least 1 (1)	0.873 (ns)	1.26 (*)	NA
Region: Other PA (0)	Southeast PA (1)	1.69 (**)	NA	NA
Organization*Region: Law Enforcement (0) * Other PA (0)	Fire/EMS (1) * Southeast PA (1)	0.446 (*)	NA	NA
	Legal (2) * Southeast PA (1)	0.532 (*)	NA	NA
	Other (3) * Southeast PA (1)	0.604 (ns)	NA	NA

P-value significance is denoted using asterisks – ns: P>0.05; *:P ≤ 0.05; *:P ≤ 0.05; **:P ≤ 0.01; ***:P ≤ 0.001.

4.0 Discussion

This analysis used ordinal logistic regression to model the relationship between demographic factors and stigma against people with Substance Use Disorders (SUD). Individual models were fit for three stigma related questions to determine which factors were predictive for stigma for each question and if the factors differed between questions. The odds of strongly agreeing with the statement, which indicates the respondent having little to no stigma, was calculated for each model.

The first question analyzed was "As a public safety professional, I have an opportunity to assist my community by connecting people to treatment for Substance Use Disorders." Organization, gender, years of experience, and region were statistically significant in this model. There was also a statistically significant interaction between organization and region. The second question analyzed was "The continued use of heroin despite the risks of overdose is an indication of Substance Use Disorder, not a wish to die." Gender, education level, and number of overdoses responded to were statistically significant in this model. The final question analyzed was "Leaving naloxone behind with overdose survivors, friends, and/or family members is the right thing to do." Organization, gender, and education level were statistically significant in the model.

The results of this study indicate that gender is consistently associated with stigma and that males are more likely to have stigma than non-males in each model. Previous studies of first responders have found contradictory results regarding the relationship between gender and stigma. One study found that males have a more positive view of SUD treatment therapies than females (Kruis et al., 2021) and another study found that gender was not significantly associated with stigma related to naloxone (Kruis et al., 2022). The results also contradict a previous study that

indicated that members of law enforcement had more positive views of naloxone, indicating less stigma, than other first responders such as fire fighters and EMS (Kruis et al., 2022). This study found that belonging to a specific professional organization does not have a consistent association with stigma and is dependent on the question asked. For example, members of law enforcement (compared to those in other organizations) were more likely to have stigma when asked about Naloxone but had similar odds of stigma compared to others when asked about their perception of continued drug use. These results also indicate that the association of professional organization with stigma may differ by region. The significance of region is supported by findings in a previous study that indicated a difference in Naloxone perceptions between rural and urban first responders (Kruis et al., 2022).

The finding that those who have never responded to an overdose are less likely to have stigma is supported in other studies (Kruis et al., 2022; Carroll et al., 2020). Additionally, multiple studies note that responding to overdose calls, and working as a first responder during the opioid epidemic, is associated with burnout and compassion fatigue among first responders. This in turn is associated with negative perceptions of SUD and hopelessness about treatment options (Carroll et al., 2020; Green et al., 2013; Pike et al., 2019). This may also explain the finding that those with less experience in their organization are less likely to have stigma, as those with less time on the job may not be experiencing burnout or related issues yet. Finally, the finding that those with higher education, and especially a graduate degree, may be less likely to have stigma than those without a college degree is consistent with another study that found that first responders with college degrees have more positive views of medication for addiction treatment (Kruis et al., 2021).

Gender is the only predictor that was statistically significant for all three questions. Outside of gender, statistically significant predictors of stigma differed by question. This suggests that even though the topics of the three questions evaluated (connection to treatment, continued drug use, and naloxone use) are all aspects of stigma against people with SUD, there are significant differences between them. However, there are some overarching themes. First, these results suggest that the likelihood of stigma does vary by professional organization so training initiatives, such as the First Responder Addiction and Connection to Treatment (FR-ACT) training program, may be more successful if they tailor the curriculum to each organization. The second finding is that more years of experience on the job and responding to overdose calls are associated with higher likelihood of stigma. A potential cause of this is professional burnout and compassion fatigue (Carroll et al., 2020; Green et al., 2013; Pike et al., 2019). In response, organizations should explore ways to best support the mental health of their people so they can continue to respond to overdoses without it negatively affecting them. Training programs should also highlight this issue and the importance of self-care. Differences in stigma by education level also support the need to tailor training sessions to the audience, even within organizations. Finally, these results indicate that training sessions should first consider which aspects of SUD stigma they wish to address and change tactics as needed, as people may react differently based on the topic.

This study is limited to the demographic factors collected in the FR-ACT pre-training survey. Going forward may be useful to expand the survey to include questions additional questions, such as political affiliation and if the respondent personally knows someone with SUD, as well as categorizing zip code data into rural, suburban, and urban locations, as other similar studies have done (Kruis et al., 2022). The other four questions in the survey could be analyzed

for additional information. Lastly, it may be useful to investigate additional ways to measure stigma using the survey format.

Ordinal logistic regression was effective for this analysis. In this study, it was necessary to retain the order of the levels of the outcome variable because each level indicated a different degree of stigma. Treating the data as ordinal, as opposed to nominal where the natural ordering would be lost, was key (Bürkner & Vuorre, 2019). Fitting separate ordinal logistic regressions for each stigma question allowed for a comparison of the statistically significant predictors between different aspects of SUD related stigma. Analyzing the stigma questions together as a cumulative Likert-scale would not have allowed for differentiation between these aspects, although it may be of additional interest in the future. A concern with ordinal logistic regression is that the proportional odds assumption is frequently violated (Harrell, 2015). Indeed, this assumption was violated in two out of three of the models in this study. However, supplementary analysis with logistic regression showed support for the result of the ordinal logistic models, suggesting that the results are still meaningful even in cases where the assumptions are violated.

5.0 Conclusion

Ordinal logistic regression was used to analyze three stigma related questions, aimed to gauge stigma against people with Substance Use Disorders held by people on the frontlines of the opioid epidemic. The results indicated that gender was the only constant predictor for stigma. Other statistically significant predictors varied depending on the topic being addressed, including organization, experience level, education level, number of overdoses responded to, and region. This suggests that training sessions aimed to reduce stigma and improve responses to opioid overdoses should adjust tactics based on the audience and stigma related topic they intend to cover.

Table 13 Counts and percents of responses for covariates using orginal survey levels

Covariate	Levels	Count (Percent)
Gender	Male	915 (60.8%)
	Female	573 (38.0%)
	Other	4 (0.3%)
	Prefer not to say	14 (0.9%)
Age (years)	Under 20	7 (0.5%)
	21-30	354 (23.5%)
	31-40	389 (25.8%)
	41-50	356 (23.6%)
	51-60	276 (18.3%)
	Over 60	119 (7.9%)
	Prefer not to say	5 (0.3%)
Race/Ethnicity	Caucasian or White	1271 (84.4%)
	Black or African American	76 (5.0%)
	Latino or Hispanic	80 (5.3%)
	Asian	7 (0.5%)
	Native American	7 (0.5%)
	Native Hawaiian or Pacific Islander	3 (0.2%)
	Other	12 (0.8%)
	Two or More	25 (1.7%)
	Prefer not to say	25 (1.7%)

Table 13 Counts and percents of responses for covariates using orginal survey levels continued

Education Level	Trade School	31 (2.1%)
	High school graduate (high school diploma or equivalent including GED)	121 (8.0%)
	Some college but no degree	220 (14.6%)
	Associate degree in college (2-year)	163 (10.8%)
	Bachelor's degree in college (4-year)	639 (42.4%)
	Graduate degree	332 (21.4%)
	Prefer not to say	9 (0.6%)
Organization	Correctional officer	134 (8.9%)
	Criminal defense attorney	41 (2.7%)
	EMS	42 (2.8%)
	Family law attorney	1 (0.1%)
	Fire department	138 (9.2%)
	Judge	2 (0.1%)
	Law enforcement	532 (35.3%)
	Probation and parole	201 (13.3%)
	Prosecutor	4 (0.3%)
	Other	411 (27.3%)
Experience in Organization (years)	Less than 1	281 (18.7%)
	1-5	276 (18.3%)
	6-10	215 (14.3%)
	More than 10	734 (48.7%)

Table 13 Counts and percents of responses for covariates using orginal survey levels continued

Overdose Calls Responded To	0	915 (60.8%)
(number)	1-5	388 (25.8%)
	6-10	77 (5.1%)
	11-20	23 (1.5%)
	More than 20	35 (2.3%)
	NA	68 (4.5%)
Region of PA	Southeast	636 (42.2%)
	Northeast	167 (11.1%)
	Southcentral	258 (17.1%)
	Northcentral	104 (6.9%)
	Southwest	95 (6.3%)
	Northwest	136 (9.0%)
	NA	110 (7.3%)

Table 14 Guide for recategorization of original levels of covariates into new covariates with collapsed levels

Variable	Original Levels	New Level (Coded)
Gender	Male	Male (0)
	Female	Other (1)
	Other	
	Prefer not to say	

Table 14 Guide for recategorization of original levels of covariates into new covariates with collapsed levels conitnued

Age (years)	Under 20	Under 40 and prefer not to say (0)
	21-30	
	31-40	40 and over (1)
	41-50	
	51-60	
	Over 60	
	Prefer not to say	
Race/Ethnicity	Caucasian or White	Caucasian or White (0)
	Black or African American	Other (1)
	Latino or Hispanic	
	Asian	
	Native American	
	Native Hawaiian or Pacific Islander	
	Other	
	Two or More	
	Prefer not to say	
Education Level	Trade School	Less than a college degree and
	High school graduate (high school diploma or equivalent including GED)	prefer not to say (0)
	Some college but no degree	Associate or bachelor's degree (1)
	Associate degree in college (2-year)	
	Bachelor's degree in college (4-year)	Graduate degree (2)
	Graduate degree	
	Prefer not to say	

Table 14 Guide for recategorization of original levels of covariates into new covariates with collapsed levels continued

Organization	Correctional officer	Law enforcement (0)
	Criminal defense attorney	Fire Department and EMS (1)
	EMS	Legal (2)
	Family law attorney	Other (3)
	Fire department	
	Judge	
	Law enforcement	
	Probation and parole	
	Prosecutor	
	Other	
Experience in Organization (years)	Less than 1	Less than 1 (0)
	1-5	1-10 (1)
	6-10	More than 10 (2)
	More than 10	
Overdose Calls Responded To (number)	0	Never responded (0)
	1-5	Responded to at least 1 (1)
	6-10	
	11-20	
	More than 20	
	NA	

Table 14 Guide for recategorization of original levels of covariates into new covariates with collapsed levels continued

Region of PA	Southeast	Other PA (0)
	Northeast	Southeast PA (1)
	Southcentral	
	Northcentral	
	Southwest	
	Northwest	
	NA	
Likert Outcome	Strongly Agree	Strongly Agree (0)
	Agree	Agree (1)
	Somewhat Agree	Somewhat Agree (2)
	Neither Agree Nor Disagree	Neutral or Disagree (3)
	Somewhat Disagree	
	Disagree	
	Strongly Disagree	

Table 15 Counts and percents of responses for original seven-level Likert scale stigma questions

Original Likert Levels	Question 1	Question 2	Question 3
	Count (Percent)		
Strongly Agree	550 (36.5%)	620 (41.2%)	416 (27.6%)
Agree	553 (35.4%)	552 (36.7%)	388 (25.8%)
Somewhat Agree	196 (13.0%)	148 (9.8%)	233 (15.5%)
Neither Agree Nor Disagree	103 (6.8%)	107 (7.1%)	278 (18.5%)
Somewhat Disagree	32 (2.1%)	21 (1.4%)	57 (3.8%)
Disagree	22 (1.5%)	12 (0.8%)	70 (4.6%)
Strongly Disagree	70 (4.6%)	46 (3.1%)	64 (4.2%)

Table 16 VIFs for covariates in question 1 ordinal model

Variable	GVIF or GVIF^(1/(2*DF) (indicated by *)
Organization	1.43*
Gender	1.27
Experience	1.09*
Overdose Responses	1.45
Region	3.17
Organization*Region	1.49*

Table 17 VIFs for covariates in question 2 ordinal model

Variable	GVIF or GVIF^(1/(2*DF) (indicated by *)
Organization	1.07*
Gender	1.21
Education	1.02*
Overdose Responses	1.23

Table 18 VIFs for covariates in question 3 ordinal model

Variable	GVIF or GVIF^(1/(2*DF) (indicated by *)
Organization	1.05*
Gender	1.24
Education	1.03*
Experience	1.03*

Appendix A.2 R Code

Appendix A.2.1 Data Preparation Code

```
# libraries
library(tidyverse)
library(knitr)
library(patchwork)
library(lubridate)
library(tidytext)
library(sjlabelled)
library(kableExtra)
library(ggpubr)
library(car)
library(foreign)
library(MASS)
library(reshape2)
library(Hmisc)
library(nnet)

# full data set as pulled on Oct. 10, 2022, starting 3/30/2021 when Likert question 7 was added
pre_sju <- read_csv("Final Dataset 2.csv", skip=2, col_names = F)

# drop CYS, they didn't get offered all the same questions in the survey as everyone else
sju_clean <- sju_clean[!(sju_clean$organization=="Children Welfare Professional/Children and
Youth"),] #1688 obs to 1550

# check missingness in predictors
sum(is.na(sju_clean$gender))
sum(is.na(sju_clean$age))
sum(is.na(sju_clean$race))
sum(is.na(sju_clean$education))
sum(is.na(sju_clean$organization))
sum(is.na(sju_clean$experience))
sum(is.na(sju_clean$zip_code)) # missing 100
sum(is.na(sju_clean$respond_overdoses)) # missing 112
# check missingness in outcomes, 44 missing for all
sum(is.na(sju_clean$L1_assist_comm))
sum(is.na(sju_clean$L2_naloxone))
sum(is.na(sju_clean$L3_cont_use))
sum(is.na(sju_clean$L4_safety))
sum(is.na(sju_clean$L5_engage))
sum(is.na(sju_clean$L6_treatable))
```

```
sum(is.na(sju_clean$L7_right))

# data cleaning: initially 1550 obs
# drop na for core likert questions
sju_clean <- sju_clean %>% drop_na(L1_assist_comm)  # down to 1506 obs, 44 people didn't
answer any likert Qs

# recheck missingness
sum(is.na(sju_clean$zip_code)) # 95 missing
sum(is.na(sju_clean$respond_overdoses)) # 68 missing

# create missingness indicator vars
sju_clean$zip_NA <- ifelse(is.na(sju_clean$zip_code), 1, 0)
sju_clean$om <- ifelse(is.na(sju_clean$respond_overdoses), 1, 0)

# Initial proportions for covariates
gen_prop <- sju_clean %>% group_by(gender) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
gen_prop1 <- kbl(gen_prop, booktabs = T, col.names = c("Gender", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
gen_prop1

sju_clean$age <- factor(sju_clean$age, levels=c("Prefer not to say","Under 20","21-30","31-
40","41-50","51-60","Over 60"))
age_prop <- sju_clean %>% group_by(age) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
age_prop1 <- kbl(age_prop, booktabs = T, col.names = c("Age Group", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
age_prop1

race_prop <- sju_clean %>% group_by(race) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
race_prop1 <- kbl(race_prop, booktabs = T, col.names = c("Race/Ethnicity", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
race_prop1

sju_clean$education <- factor(sju_clean$education, levels=c("Prefer not to say","Trade
school","High school graduate (high school diploma or equivalent including GED)","Some
college but no degree","Associate degree in college (2-year)","Bachelor's degree in college (4-
year)","Graduate degree"))
edu_prop <- sju_clean %>% group_by(education) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
edu_prop1 <- kbl(edu_prop, booktabs = T, col.names = c("Education Level", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
edu_prop1
```

```
org_prop <- sju_clean %>% group_by(organization) %>% summarize(n = n()) %>%
mutate(prop = round(n/sum(n), 3))
org_prop1 <- kbl(org_prop, booktabs = T, col.names = c("Organization", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
org_prop1

sju_clean$experience <- factor(sju_clean$experience, levels=c("Less than 1 year","1-5
years","6-10 years","More than 10 years"))
exp_prop <- sju_clean %>% group_by(experience) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
exp_prop1 <- kbl(exp_prop, booktabs = T, col.names = c("Year of Experience in Organization",
"Count", "Proportion")) %>% kable_styling(latex_options="striped")
exp_prop1

sju_clean$respond_overdoses <- factor(sju_clean$respond_overdoses, levels=c("0","1-5","6-
10","11-20","More than 20"))
over_prop <- sju_clean %>% group_by(respond_overdoses) %>% summarize(n = n()) %>%
mutate(prop = round(n/sum(n), 3))
over_prop1 <- kbl(over_prop, booktabs = T, col.names = c("Number of Overdose Calls
Responded To", "Count", "Proportion")) %>% kable_styling(latex_options="striped")
over_prop1

om_prop <- sju_clean %>% group_by(om) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
om_prop1 <- kbl(om_prop, booktabs = T, col.names = c("Missing", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
om_prop1

sju_clean$region <- factor(sju_clean$region,
levels=c("Southeast","Northeast","Southcentral","Northcentral","Southwest", "Northwest"))
reg_prop <- sju_clean %>% group_by(region) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
reg_prop1 <- kbl(reg_prop, booktabs = T, col.names = c("Region of PA", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
reg_prop1

zipNA_prop <- sju_clean %>% group_by(zip_NA) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
zipNA_prop1 <- kbl(zipNA_prop, booktabs = T, col.names = c("Missing", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
zipNA_prop1
# dichotomizing variables
# dichotomize gender male = 0, other = 1
sju_clean$gen_d <- case_when(sju_clean$gender=="Male" ~ '0', TRUE ~ '1')
# dichotomize age  under 40 = 0 , over 40 = 1
sju_clean$age_d <- case_when(sju_clean$age=="41-50" ~ '1',
```

```
                sju_clean$age=="51-60" ~ '1',
                sju_clean$age=="Over 60" ~ '1',
                TRUE ~ '0')
# dichotomize race white = 0, other = 1
sju_clean$race_d <- case_when(sju_clean$race=="Caucasian or White" ~ '0', TRUE ~ '1')
# dichotomize overdose, 0 = 0, more than 0 = 1
sju_clean$over_d <- case_when(sju_clean$respond_overdoses=="1-5" ~ '1',
                sju_clean$respond_overdoses=="6-10" ~ '1',
                sju_clean$respond_overdoses=="11-20" ~ '1',
                sju_clean$respond_overdoses=="More than 20" ~ '1',
                TRUE ~ '0')
# dichotomize region southeast = 1, other = 0
sju_clean$reg_d <- case_when(sju_clean$region=="Southeast" ~ '1',
                TRUE ~ '0')
# collapse categories
# organization
# law enforcement = 0, first responders = 1, legal = 2, other =3
sju_clean$org_cat <- case_when(sju_clean$organization=="Correctional officer" ~ '2',
        sju_clean$organization=="Criminal defense attorney" ~ '2',
        sju_clean$organization=="EMS" ~ '1',
        sju_clean$organization=="Family law attorney" ~ '2',
        sju_clean$organization=="Fire department" ~ '1',
        sju_clean$organization=="Judge" ~ '2',
        sju_clean$organization=="Other" ~ '3',
        sju_clean$organization=="Probation and parole" ~ '2',
        sju_clean$organization=="Prosecutor" ~ '2',
        TRUE ~ '0')

# education categories
#less than college degree = 0, bachelors/associates = 1, graduate degree 2
sju_clean$edu_cat <- case_when(sju_clean$education=="Bachelor's degree in college (4-year)"
~ '1',
        sju_clean$education=="Graduate degree" ~ '2',
        sju_clean$education=="Associate degree in college (2-year)" ~ '1',
                TRUE ~ '0')
# categorize years of experience
# less than 1 = 0, 1-10 = 1, over 10 = 2
sju_clean$exp_cat <- case_when(sju_clean$experience=="More than 10 years" ~ '2',
            sju_clean$experience=="Less than 1 year" ~ '0',
                TRUE ~ '1')
# New proportions for covariates
gen_d_prop <- sju_clean %>% group_by(gen_d) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
gen_d_prop <- gen_d_prop %>% mutate(gen_d=recode_factor(gen_d, `0` = "Male", `1`=
"Other"))
```

```
gen_d_prop1 <- kbl(gen_d_prop, booktabs = T, col.names = c("Gender", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
gen_d_prop1

age_d_prop <- sju_clean %>% group_by(age_d) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
age_d_prop <- age_d_prop %>% mutate(age_d=recode_factor(age_d, `0` = "Under 40", `1`=
"40+"))
age_d_prop1 <- kbl(age_d_prop, booktabs = T, col.names = c("Age", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
age_d_prop1

race_d_prop <- sju_clean %>% group_by(race_d) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
race_d_prop <- race_d_prop %>% mutate(race_d=recode_factor(race_d, `0` =
"White/Caucasian", `1`= "Other"))
race_d_prop1 <- kbl(race_d_prop, booktabs = T, col.names = c("Race/Ethnicity", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
race_d_prop1

edu_cat_prop <- sju_clean %>% group_by(edu_cat) %>% summarize(n = n()) %>%
mutate(prop = round(n/sum(n), 3))
edu_cat_prop <- edu_cat_prop %>% mutate(edu_cat=recode_factor(edu_cat, `0` = "Less than
college", `1`= "Assoc./Bach. degree", `2` = "Grad. degree"))
edu_cat_prop1 <- kbl(edu_cat_prop, booktabs = T, col.names = c("Education Level", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
edu_cat_prop1

org_cat_prop <- sju_clean %>% group_by(org_cat) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
org_cat_prop <- org_cat_prop %>% mutate(org_cat=recode_factor(org_cat, `0` = "Law enforc.",
`1`= "Fire/EMS", `2` = "Legal", `3` = "Other"))
org_cat_prop1 <- kbl(org_cat_prop, booktabs = T, col.names = c("Organization", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
org_cat_prop1

exp_cat_prop <- sju_clean %>% group_by(exp_cat) %>% summarize(n = n()) %>%
mutate(prop = round(n/sum(n), 3))
exp_cat_prop <- exp_cat_prop %>% mutate(exp_cat=recode_factor(exp_cat, `0` = "<1 Year",
`1`= "1-10 Years", `2` = "10+ Years"))
exp_cat_prop1<- kbl(exp_cat_prop, booktabs = T, col.names = c("Experience Level", "Count",
"Proportion")) %>% kable_styling(latex_options="striped")
exp_cat_prop1

over_d_prop <- sju_clean %>% group_by(over_d) %>% summarize(n = n()) %>% mutate(prop
= round(n/sum(n), 3))
```

```
over_d_prop <- over_d_prop %>% mutate(over_d=recode_factor(over_d, `0` = "Never
responded to an overdose", `1`= "Responded to at least 1 overdose"))
over_d_prop1 <- kbl(over_d_prop, booktabs = T, col.names = c("Number of Overdoses Calls",
"Count", "Proportion")) %>% kable_styling(latex_options="striped")
over_d_prop1

reg_d_prop <- sju_clean %>% group_by(reg_d) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))
reg_d_prop <- reg_d_prop %>% mutate(reg_d=recode_factor(reg_d, `0` = "Other PA", `1`=
"Southeast PA"))
reg_d_prop1 <- kbl(reg_d_prop, booktabs = T, col.names = c("Region", "Count", "Proportion"))
%>% kable_styling(latex_options="striped")
reg_d_prop1

#initial proportions for Likert outcomes
sju_clean$L1_assist_comm <- factor(sju_clean$L1_assist_comm , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L2_naloxone <- factor(sju_clean$L2_naloxone, levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L3_cont_use <- factor(sju_clean$L3_cont_use , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L4_safety <- factor(sju_clean$L4_safety , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L5_engage<- factor(sju_clean$L5_engage , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L6_treatable <- factor(sju_clean$L6_treatable , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
sju_clean$L7_right <- factor(sju_clean$L7_right , levels=c("Strongly
agree","Agree","Somewhat agree","Neither agree nor disagree","Somewhat
disagree","Disagree","Strongly disagree"))
L1 <- prop.table(table(sju_clean$L1_assist_comm)) %>% round(2)
L2 <- prop.table(table(sju_clean$L2_naloxone)) %>% round(2)
L3 <- prop.table(table(sju_clean$L3_cont_use)) %>% round(2)
L4 <- prop.table(table(sju_clean$L4_safety)) %>% round(2)
L5 <- prop.table(table(sju_clean$L5_engage)) %>% round(2)
L6 <- prop.table(table(sju_clean$L6_treatable)) %>% round(2)
L7 <- prop.table(table(sju_clean$L7_right)) %>% round(2)
likert_tab_1 <- t(rbind(L1, L2, L3, L4, L5, L6, L7))
likert_tab_2 <- kbl(likert_tab_1, booktabs = T) %>% kable_styling(latex_options="striped")
likert_tab_2
```

```
L <- sju_clean %>% group_by(L7_right) %>% summarize(n = n()) %>% mutate(prop =
round(n/sum(n), 3))

# collapse likert scale
# grouping all disagree levels and neutral, all agree levels stay separate
# strongly agree is reference category (0)
sju_clean$L1_2 <- case_when(sju_clean$L1_assist_comm=="Strongly disagree" ~ '3',
                sju_clean$L1_assist_comm=="Disagree" ~ '3',
             sju_clean$L1_assist_comm=="Somewhat disagree" ~ '3',
          sju_clean$L1_assist_comm=="Neither agree nor disagree" ~ '3',
                sju_clean$L1_assist_comm=="Somewhat agree" ~ '2',
                sju_clean$L1_assist_comm=="Agree" ~ '1',
                TRUE ~ '0')
sju_clean$L3_2 <- case_when(sju_clean$L3_cont_use=="Strongly disagree" ~ '3',
                sju_clean$L3_cont_use=="Disagree" ~ '3',
                sju_clean$L3_cont_use=="Somewhat disagree" ~ '3',
             sju_clean$L3_cont_use=="Neither agree nor disagree" ~ '3',
                sju_clean$L3_cont_use=="Somewhat agree" ~ '2',
                sju_clean$L3_cont_use=="Agree" ~ '1',
                TRUE ~ '0')
sju_clean$L7_2 <- case_when(sju_clean$L7_right=="Strongly disagree" ~ '3',
                sju_clean$L7_right=="Disagree" ~ '3',
                sju_clean$L7_right=="Somewhat disagree" ~ '3',
             sju_clean$L7_right=="Neither agree nor disagree" ~ '3',
                sju_clean$L7_right=="Somewhat agree" ~ '2',
                sju_clean$L7_right=="Agree" ~ '1',
                TRUE ~ '0')

# proportion of responses for each question
sju_clean$L1_2 <- factor(sju_clean$L1_2 , levels=c("0", "1", "2", "3"))
sju_clean$L3_2 <- factor(sju_clean$L3_2, levels=c("0", "1", "2", "3"))
sju_clean$L7_2 <- factor(sju_clean$L7_2 , levels=c("0", "1", "2", "3"))
L1_2 <- prop.table(table(sju_clean$L1_2)) %>% round(2)
L3_2 <- prop.table(table(sju_clean$L3_2)) %>% round(2)
L7_2 <- prop.table(table(sju_clean$L7_2)) %>% round(2)
likert_tab_5 <- t(rbind(L1_2, L3_2, L7_2))
likert_tab_6 <- kbl(likert_tab_5, booktabs = T, caption = "0 is strongly agree, 1 is agree, 2 is
somewhat agree, 3 is neither agree nor disagree and any disagree") %>%
kable_styling(latex_options="striped")
likert_tab_6
write.csv(sju_clean, "Clean Capstone Data Final Version.csv", row.names=TRUE)
```

Appendix A.2.2 Bivariate Descriptives

```
# organization, can repeat for all covarites
chisq.test(table(sju$org_cat,  sju$age_d), correct=FALSE) # correlated
chisq.test(table(sju$org_cat,  sju$race_d), correct=FALSE)
chisq.test(table(sju$org_cat,  sju$edu_cat), correct=FALSE) # correlated
chisq.test(table(sju$org_cat,  sju$exp_cat), correct=FALSE) # correlated
chisq.test(table(sju$org_cat,  sju$gen_d), correct=FALSE) # correlated
chisq.test(table(sju$org_cat,  sju$over_d), correct=FALSE) # correlated
chisq.test(table(sju$org_cat,  sju$reg_d), correct=FALSE) # correlated

#ex: age
chisq.test(table(sju$age_d,  sju$race_d), correct=FALSE)
chisq.test(table(sju$age_d,  sju$edu_cat), correct=FALSE) # correlated
chisq.test(table(sju$age_d,  sju$exp_cat), correct=FALSE) #correlated
chisq.test(table(sju$age_d,  sju$org_cat), correct=FALSE) #correlated
chisq.test(table(sju$age_d,  sju$over_d), correct=FALSE)
chisq.test(table(sju$age_d,  sju$reg_d), correct=FALSE)

# chi-sq of homogeneity/independence for L1
chisq.test(table(sju$gen_d,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$age_d,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$race_d,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$edu_cat,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$org_cat,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$exp_cat,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$over_d,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$om,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$reg_d,  sju$L1_2), correct=FALSE)
chisq.test(table(sju$zip_NA,  sju$L1_2), correct=FALSE)

# chi-sq of homogeneity/independence for L3
chisq.test(table(sju$gen_d,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$age_d,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$race_d,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$edu_cat,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$org_cat,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$exp_cat,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$over_d,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$om,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$reg_d,  sju$L3_2), correct=FALSE)
chisq.test(table(sju$zip_NA,  sju$L3_2), correct=FALSE)

# chi-sq of homogeneity/independence for L7
chisq.test(table(sju$gen_d,  sju$L7_2), correct=FALSE)
```

```
chisq.test(table(sju$age_d,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$race_d,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$edu_cat,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$org_cat,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$exp_cat,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$over_d,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$om,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$reg_d,  sju$L7_2), correct=FALSE)
chisq.test(table(sju$zip_NA,  sju$L7_2), correct=FALSE)
```

Appendix A.2.3 Univariate Analysis

```
##L1
L1data <- sju[, c("gen_d", "age_d", "race_d", "edu_cat", "org_cat", "exp_cat", "over_d", "reg_d",
"zip_NA", "om", "L1_2")]
L1data$L1_2 <- factor(L1data$L1_2 )

## fit ordered logit model and store results 'm'
## Hess=TRUE to have the model return the observed information matrix from optimization
(called the Hessian) which is used to get standard errors
m_org <- polr(L1_2 ~ factor(org_cat) , data = L1data, Hess=TRUE)
## store table
ctable1 <- coef(summary(m_org))
## calculate and store p values
p <- pnorm(abs(ctable1[, "t value"]), lower.tail = FALSE) * 2
## combined table
(ctable1 <- cbind(ctable1, "p value" = p))
ci_org <- confint(m_org)
# odds ratios
(exp(cbind(OR = coef(m_org), ci_org)))

m_gen <- polr(L1_2 ~ factor(gen_d) , data = L1data, Hess=TRUE)
ctable3 <- coef(summary(m_gen))
p <- pnorm(abs(ctable3[, "t value"]), lower.tail = FALSE) * 2
(ctable3 <- cbind(ctable3, "p value" = p))
ci_gen <- confint(m_gen)
# odds ratios
(exp(cbind(OR = coef(m_gen), ci_gen)))

m_age <- polr(L1_2 ~ factor(age_d) , data = L1data, Hess=TRUE)
ctable4 <- coef(summary(m_age))
p <- pnorm(abs(ctable4[, "t value"]), lower.tail = FALSE) * 2
(ctable4 <- cbind(ctable4, "p value" = p))
```

```r
ci_age <- confint(m_age)
# odds ratios
(exp(cbind(OR = coef(m_age), ci_age)))

m_race <- polr(L1_2 ~ factor(race_d) , data = L1data, Hess=TRUE)
ctable5 <- coef(summary(m_race))
p <- pnorm(abs(ctable5[, "t value"]), lower.tail = FALSE) * 2
(ctable5 <- cbind(ctable5, "p value" = p))
ci_race <- confint(m_race)
# odds ratios
(exp(cbind(OR = coef(m_race), ci_race)))

m_edu <- polr(L1_2 ~ factor(edu_cat) , data = L1data, Hess=TRUE)
ctable6 <- coef(summary(m_edu))
p <- pnorm(abs(ctable6[, "t value"]), lower.tail = FALSE) * 2
(ctable6 <- cbind(ctable6, "p value" = p))
ci_edu <- confint(m_edu)
# odds ratios
(exp(cbind(OR = coef(m_edu), ci_edu)))

m_exp <- polr(L1_2 ~ factor(exp_cat) , data = L1data, Hess=TRUE)
ctable7 <- coef(summary(m_exp))
p <- pnorm(abs(ctable7[, "t value"]), lower.tail = FALSE) * 2
(ctable7 <- cbind(ctable7, "p value" = p))
ci_exp <- confint(m_exp)
# odds ratios
(exp(cbind(OR = coef(m_exp), ci_exp)))

m_over <- polr(L1_2 ~ factor(over_d) , data = L1data, Hess=TRUE)
ctable8 <- coef(summary(m_over))
p <- pnorm(abs(ctable8[, "t value"]), lower.tail = FALSE) * 2
(ctable8 <- cbind(ctable8, "p value" = p))
ci_over <- confint(m_over)
# odds ratios
(exp(cbind(OR = coef(m_over), ci_over)))

m_om <- polr(L1_2 ~ factor(om) , data = L1data, Hess=TRUE)
ctableom <- coef(summary(m_om))
p <- pnorm(abs(ctableom[, "t value"]), lower.tail = FALSE) * 2
(ctableom <- cbind(ctableom, "p value" = p))
ci_om <- confint(m_om)
# odds ratios
(exp(cbind(OR = coef(m_om), ci_om)))

m_reg <- polr(L1_2 ~ factor(reg_d) , data = L1data, Hess=TRUE)
ctable9 <- coef(summary(m_reg))
```

```
p <- pnorm(abs(ctable9[, "t value"]), lower.tail = FALSE) * 2
(ctable9 <- cbind(ctable9, "p value" = p))
ci_reg <- confint(m_reg)
# odds ratios
(exp(cbind(OR = coef(m_reg), ci_reg)))


m_mis <- polr(L1_2 ~ factor(zip_NA) , data = L1data, Hess=TRUE)
ctable10 <- coef(summary(m_mis))
p <- pnorm(abs(ctable10[, "t value"]), lower.tail = FALSE) * 2
(ctable10 <- cbind(ctable10, "p value" = p))
ci_mis <- confint(m_mis)
# odds ratios
(exp(cbind(OR = coef(m_mis), ci_mis)))


##L3
L3data <- sju[, c("gen_d", "age_d", "race_d", "edu_cat", "org_cat", "exp_cat", "over_d", "reg_d",
"zip_NA", "om", "L3_2")]
L3data$L3_2 <- factor(L3data$L3_2 )


## fit ordered logit model and store results 'm'
## Hess=TRUE to have the model return the observed information matrix from optimization
(called the Hessian) which is used to get standard errors
m_org <- polr(L3_2 ~ factor(org_cat) , data = L3data, Hess=TRUE)
## store table
ctable1 <- coef(summary(m_org))
## calculate and store p values
p <- pnorm(abs(ctable1[, "t value"]), lower.tail = FALSE) * 2
## combined table
(ctable1 <- cbind(ctable1, "p value" = p))
ci_org <- confint(m_org)
# odds ratios
(exp(cbind(OR = coef(m_org), ci_org)))


m_gen <- polr(L3_2 ~ factor(gen_d) , data = L3data, Hess=TRUE)
ctable3 <- coef(summary(m_gen))
p <- pnorm(abs(ctable3[, "t value"]), lower.tail = FALSE) * 2
(ctable3 <- cbind(ctable3, "p value" = p))
ci_gen <- confint(m_gen)
# odds ratios
(exp(cbind(OR = coef(m_gen), ci_gen)))


m_age <- polr(L3_2 ~ factor(age_d) , data = L3data, Hess=TRUE)
ctable4 <- coef(summary(m_age))
p <- pnorm(abs(ctable4[, "t value"]), lower.tail = FALSE) * 2
(ctable4 <- cbind(ctable4, "p value" = p))
ci_age <- confint(m_age)
```

```
# odds ratios
(exp(cbind(OR = coef(m_age), ci_age)))

m_race <- polr(L3_2 ~ factor(race_d) , data = L3data, Hess=TRUE)
ctable5 <- coef(summary(m_race))
p <- pnorm(abs(ctable5[, "t value"]), lower.tail = FALSE) * 2
(ctable5 <- cbind(ctable5, "p value" = p))
ci_race <- confint(m_race)
# odds ratios
(exp(cbind(OR = coef(m_race), ci_race)))

m_edu <- polr(L3_2 ~ factor(edu_cat) , data = L3data, Hess=TRUE)
ctable6 <- coef(summary(m_edu))
p <- pnorm(abs(ctable6[, "t value"]), lower.tail = FALSE) * 2
(ctable6 <- cbind(ctable6, "p value" = p))
ci_edu <- confint(m_edu)
# odds ratios
(exp(cbind(OR = coef(m_edu), ci_edu)))

m_exp <- polr(L3_2 ~ factor(exp_cat) , data = L3data, Hess=TRUE)
ctable7 <- coef(summary(m_exp))
p <- pnorm(abs(ctable7[, "t value"]), lower.tail = FALSE) * 2
(ctable7 <- cbind(ctable7, "p value" = p))
ci_exp <- confint(m_exp)
# odds ratios
(exp(cbind(OR = coef(m_exp), ci_exp)))

m_over <- polr(L3_2 ~ factor(over_d) , data = L3data, Hess=TRUE)
ctable8 <- coef(summary(m_over))
p <- pnorm(abs(ctable8[, "t value"]), lower.tail = FALSE) * 2
(ctable8 <- cbind(ctable8, "p value" = p))
ci_over <- confint(m_over)
# odds ratios
(exp(cbind(OR = coef(m_over), ci_over)))

m_om <- polr(L3_2 ~ factor(om) , data = L3data, Hess=TRUE)
ctableom <- coef(summary(m_om))
p <- pnorm(abs(ctableom[, "t value"]), lower.tail = FALSE) * 2
(ctableom <- cbind(ctableom, "p value" = p))
ci_om <- confint(m_om)
# odds ratios
(exp(cbind(OR = coef(m_om), ci_om)))

m_reg <- polr(L3_2 ~ factor(reg_d) , data = L3data, Hess=TRUE)
ctable9 <- coef(summary(m_reg))
p <- pnorm(abs(ctable9[, "t value"]), lower.tail = FALSE) * 2
```

```
(ctable9 <- cbind(ctable9, "p value" = p))
ci_reg <- confint(m_reg)
# odds ratios
(exp(cbind(OR = coef(m_reg), ci_reg)))

m_mis <- polr(L3_2 ~ factor(zip_NA) , data = L3data, Hess=TRUE)
ctable10 <- coef(summary(m_mis))
p <- pnorm(abs(ctable10[, "t value"]), lower.tail = FALSE) * 2
(ctable10 <- cbind(ctable10, "p value" = p))
ci_mis <- confint(m_mis)
# odds ratios
(exp(cbind(OR = coef(m_mis), ci_mis)))

##L7
L7data <- sju[, c("gen_d", "age_d", "race_d", "edu_cat", "org_cat", "exp_cat", "over_d", "reg_d",
"zip_NA", "om", "L7_2")]
L7data$L7_2 <- factor(L7data$L7_2 )

## fit ordered logit model and store results 'm'
## Hess=TRUE to have the model return the observed information matrix from optimization
(called the Hessian) which is used to get standard errors
m_org <- polr(L7_2 ~ factor(org_cat) , data = L7data, Hess=TRUE)
## store table
ctable1 <- coef(summary(m_org))
## calculate and store p values
p <- pnorm(abs(ctable1[, "t value"]), lower.tail = FALSE) * 2
## combined table
(ctable1 <- cbind(ctable1, "p value" = p))
ci_org <- confint(m_org)
# odds ratios
(exp(cbind(OR = coef(m_org), ci_org)))

m_gen <- polr(L7_2 ~ factor(gen_d) , data = L7data, Hess=TRUE)
ctable3 <- coef(summary(m_gen))
p <- pnorm(abs(ctable3[, "t value"]), lower.tail = FALSE) * 2
(ctable3 <- cbind(ctable3, "p value" = p))
ci_gen <- confint(m_gen)
# odds ratios
(exp(cbind(OR = coef(m_gen), ci_gen)))

m_age <- polr(L7_2 ~ age_d , data = L7data, Hess=TRUE)
ctable4 <- coef(summary(m_age))
p <- pnorm(abs(ctable4[, "t value"]), lower.tail = FALSE) * 2
(ctable4 <- cbind(ctable4, "p value" = p))
ci_age <- confint(m_age)
# odds ratios
```

```
(exp(cbind(OR = coef(m_age), ci_age)))

m_race <- polr(L7_2 ~ factor(race_d) , data = L7data, Hess=TRUE)
ctable5 <- coef(summary(m_race))
p <- pnorm(abs(ctable5[, "t value"]), lower.tail = FALSE) * 2
(ctable5 <- cbind(ctable5, "p value" = p))
ci_race <- confint(m_race)
# odds ratios
(exp(cbind(OR = coef(m_race), ci_race)))

m_edu <- polr(L7_2 ~ factor(edu_cat) , data = L7data, Hess=TRUE)
ctable6 <- coef(summary(m_edu))
p <- pnorm(abs(ctable6[, "t value"]), lower.tail = FALSE) * 2
(ctable6 <- cbind(ctable6, "p value" = p))
ci_edu <- confint(m_edu)
# odds ratios
(exp(cbind(OR = coef(m_edu), ci_edu)))

m_exp <- polr(L7_2 ~ factor(exp_cat) , data = L7data, Hess=TRUE)
ctable7 <- coef(summary(m_exp))
p <- pnorm(abs(ctable7[, "t value"]), lower.tail = FALSE) * 2
(ctable7 <- cbind(ctable7, "p value" = p))
ci_exp <- confint(m_exp)
# odds ratios
(exp(cbind(OR = coef(m_exp), ci_exp)))

m_over <- polr(L7_2 ~ factor(over_d) , data = L7data, Hess=TRUE)
ctable8 <- coef(summary(m_over))
p <- pnorm(abs(ctable8[, "t value"]), lower.tail = FALSE) * 2
(ctable8 <- cbind(ctable8, "p value" = p))
ci_over <- confint(m_over)
# odds ratios
(exp(cbind(OR = coef(m_over), ci_over)))

m_om <- polr(L7_2 ~ factor(om) , data = L7data, Hess=TRUE)
ctableom <- coef(summary(m_om))
p <- pnorm(abs(ctableom[, "t value"]), lower.tail = FALSE) * 2
(ctableom <- cbind(ctableom, "p value" = p))
ci_om <- confint(m_om)
# odds ratios
(exp(cbind(OR = coef(m_om), ci_om)))

m_reg <- polr(L7_2 ~ factor(reg_d) , data = L7data, Hess=TRUE)
ctable9 <- coef(summary(m_reg))
p <- pnorm(abs(ctable9[, "t value"]), lower.tail = FALSE) * 2
(ctable9 <- cbind(ctable9, "p value" = p))
```

```
ci_reg <- confint(m_reg)
# odds ratios
(exp(cbind(OR = coef(m_reg), ci_reg)))

m_mis <- polr(L7_2 ~ factor(zip_NA) , data = L7data, Hess=TRUE)
ctable10 <- coef(summary(m_mis))
p <- pnorm(abs(ctable10[, "t value"]), lower.tail = FALSE) * 2
(ctable10 <- cbind(ctable10, "p value" = p))
ci_mis <- confint(m_mis)
# odds ratios
(exp(cbind(OR = coef(m_mis), ci_mis)))
```

Appendix A.2.4 Model Selection

```
## L1
#Initial model based on univariate
m1  <-  polr(L1_2  ~  factor(org_cat)  +  factor(gen_d)  +  factor(edu_cat)  +  factor(exp_cat)+
factor(over_d), data = L1data, Hess=TRUE)
summary(m1)
ctable_1 <- coef(summary(m1))
p <- pnorm(abs(ctable_1[, "t value"]), lower.tail = FALSE) * 2
(ctable_1 <- cbind(ctable_1, "p value" = p))

# check overdose is needed
m2 <- polr(L1_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(exp_cat), data =
L1data, Hess=TRUE)
summary(m2)
ctable_2 <- coef(summary(m2))
p <- pnorm(abs(ctable_2[, "t value"]), lower.tail = FALSE) * 2
(ctable_2 <- cbind(ctable_2, "p value" = p))
#overdose not significant but confounds org, need to keep

# check experience is needed
m3 <- polr(L1_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d), data =
L1data, Hess=TRUE)
summary(m3)
ctable_3 <- coef(summary(m3))
p <- pnorm(abs(ctable_3[, "t value"]), lower.tail = FALSE) * 2
(ctable_3 <- cbind(ctable_3, "p value" = p))
# should keep experience

# check education is needed
m4 <- polr(L1_2 ~ factor(org_cat) + factor(gen_d) + factor(exp_cat) + factor(over_d), data =
L1data, Hess=TRUE)
```

```
summary(m4)
ctable_4 <- coef(summary(m4))
p <- pnorm(abs(ctable_4[, "t value"]), lower.tail = FALSE) * 2
(ctable_4 <- cbind(ctable_4, "p value" = p))
# education not significant, not confounding, can remove


# check gender is needed
m5 <- polr(L1_2 ~ factor(org_cat) + factor(exp_cat) + factor(over_d), data = L1data, Hess=TRUE)
summary(m5)
ctable_5 <- coef(summary(m5))
p <- pnorm(abs(ctable_5[, "t value"]), lower.tail = FALSE) * 2
(ctable_5 <- cbind(ctable_5, "p value" = p))
# should keep gender, significant


# check experience is needed
m6 <- polr(L1_2 ~ factor(org_cat)+ factor(gen_d) + factor(over_d), data = L1data, Hess=TRUE)
summary(m6)
ctable_6 <- coef(summary(m6))
p <- pnorm(abs(ctable_6[, "t value"]), lower.tail = FALSE) * 2
(ctable_6 <- cbind(ctable_6, "p value" = p))
# should keep experience, significant


# check org is needed
m7 <- polr(L1_2 ~ factor(gen_d) + factor(exp_cat) + factor(over_d), data = L1data, Hess=TRUE)
summary(m7)
ctable_7 <- coef(summary(m7))
p <- pnorm(abs(ctable_7[, "t value"]), lower.tail = FALSE) * 2
(ctable_7 <- cbind(ctable_7, "p value" = p))
# should keep org, significant


## ADD BACK IN UNUSED VARS TO CHECK
# check race is needed
m4_1 <- polr(L1_2 ~ factor(org_cat) + factor(gen_d) + factor(exp_cat) + factor(over_d) +
factor(race_d), data = L1data, Hess=TRUE)
summary(m4_1)
ctable_4_1 <- coef(summary(m4_1))
p <- pnorm(abs(ctable_4_1[, "t value"]), lower.tail = FALSE) * 2
(ctable_4_1 <- cbind(ctable_4_1, "p value" = p))
# race not sig, not a confounder


# check region is needed, again
m4_3 <- polr(L1_2 ~ factor(org_cat) + factor(gen_d) + factor(exp_cat) + factor(over_d) +
factor(reg_d), data = L1data, Hess=TRUE)
summary(m4_3)
ctable_4_3 <- coef(summary(m4_3))
p <- pnorm(abs(ctable_4_3[, "t value"]), lower.tail = FALSE) * 2
```

```
(ctable_4_3 <- cbind(ctable_4_3, "p value" = p))
# reg not significant, but is a confounder for org, need to keep


## CHECK INTERACTIONS WIHT ORG
# check org*gen
m8 <- polr(L1_2 ~ factor(org_cat)*factor(gen_d) + factor(exp_cat) + factor(over_d) +
factor(reg_d), data = L1data, Hess=TRUE)
summary(m8)
ctable_8 <- coef(summary(m8))
p <- pnorm(abs(ctable_8[, "t value"]), lower.tail = FALSE) * 2
ctable_8 <- cbind(ctable_8, "p value" = p)
 # interaction not needed


# check org*exp
m9 <- polr(L1_2 ~ factor(org_cat)*factor(exp_cat) + factor(gen_d) + factor(over_d) +
factor(reg_d), data = L1data, Hess=TRUE)
summary(m9)
ctable_9 <- coef(summary(m9))
p <- pnorm(abs(ctable_9[, "t value"]), lower.tail = FALSE) * 2
ctable_9 <- cbind(ctable_9, "p value" = p)
# interaction not needed


# check org*overdose
m10 <- polr(L1_2 ~ factor(org_cat)*factor(over_d) + factor(gen_d) + factor(exp_cat) +
factor(reg_d), data = L1data, Hess=TRUE)
summary(m10)
ctable_10 <- coef(summary(m10))
p <- pnorm(abs(ctable_10[, "t value"]), lower.tail = FALSE) * 2
ctable_10 <- cbind(ctable_10, "p value" = p)
# interaction not needed


# check org*overdose
m11 <- polr(L1_2 ~ factor(org_cat)*factor(reg_d) + factor(gen_d) + factor(exp_cat) +
factor(over_d), data = L1data, Hess=TRUE)
summary(m11)
ctable_11 <- coef(summary(m11))
p <- pnorm(abs(ctable_11[, "t value"]), lower.tail = FALSE) * 2
(ctable_11 <- cbind(ctable_11, "p value" = p))
# interaction significant

## this is final model, model 11 is best
#check collinearity
vif(m11)
# odds ratios for final model (m11)
(ci_m11 <- confint(m11))
(exp(cbind(OR = coef(m11), ci_m11)))
```

```
## L3
# Initial model based on univariate
m1 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d) , data =
L3data, Hess=TRUE)
summary(m1)
ctable_1 <- coef(summary(m1))
p <- pnorm(abs(ctable_1[, "t value"]), lower.tail = FALSE) * 2
(ctable_1 <- cbind(ctable_1, "p value" = p))

# check overdose is needed
m2 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) , data = L3data, Hess=TRUE)
summary(m2)
ctable_2 <- coef(summary(m2))
p <- pnorm(abs(ctable_2[, "t value"]), lower.tail = FALSE) * 2
(ctable_2 <- cbind(ctable_2, "p value" = p))
# should keep overdose, significant

# check education is needed
m3 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(over_d) , data = L3data, Hess=TRUE)
summary(m3)
ctable_3 <- coef(summary(m3))
p <- pnorm(abs(ctable_3[, "t value"]), lower.tail = FALSE) * 2
(ctable_3 <- cbind(ctable_3, "p value" = p))
# should keep education, very significant

# check gender is needed
m4 <- polr(L3_2 ~ factor(org_cat) + factor(edu_cat) + factor(over_d) , data = L3data,
Hess=TRUE)
summary(m4)
ctable_4 <- coef(summary(m4))
p <- pnorm(abs(ctable_4[, "t value"]), lower.tail = FALSE) * 2
(ctable_4 <- cbind(ctable_4, "p value" = p))
# should keep gender, significant

# check org is needed
m5 <- polr(L3_2 ~ factor(gen_d) + factor(edu_cat) + factor(over_d) , data = L3data, Hess=TRUE)
summary(m5)
ctable_5 <- coef(summary(m5))
p <- pnorm(abs(ctable_5[, "t value"]), lower.tail = FALSE) * 2
(ctable_5 <- cbind(ctable_5, "p value" = p))
# org is not significant but main predictor so keeping anyway

## Add Back in Excluded Vars
# add in race
```

```r
m1_2 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d) +
factor(race_d) , data = L3data, Hess=TRUE)
summary(m1_2)
ctable_1_2 <- coef(summary(m1_2))
p <- pnorm(abs(ctable_1_2[, "t value"]), lower.tail = FALSE) * 2
(ctable_1_2 <- cbind(ctable_1_2, "p value" = p))
# not signif., not confounding

# add in experience
# note possible confounding with region
m1_3 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d) +
factor(exp_cat) , data = L3data, Hess=TRUE)
summary(m1_3)
ctable_1_3 <- coef(summary(m1_3))
p <- pnorm(abs(ctable_1_3[, "t value"]), lower.tail = FALSE) * 2
(ctable_1_3 <- cbind(ctable_1_3, "p value" = p))
# not signif., not confounding

# add in region
m1_4 <- polr(L3_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d) +
factor(reg_d) , data = L3data, Hess=TRUE)
summary(m1_4)
ctable_1_4 <- coef(summary(m1_4))
p <- pnorm(abs(ctable_1_4[, "t value"]), lower.tail = FALSE) * 2
(ctable_1_4 <- cbind(ctable_1_4, "p value" = p))
# not signif., not counfounding

## Check Interactions
# check org*gen
m6 <- polr(L3_2 ~ factor(org_cat)*factor(gen_d) + factor(edu_cat) + factor(over_d) , data =
L3data, Hess=TRUE)
summary(m6)
ctable_6 <- coef(summary(m6))
p <- pnorm(abs(ctable_6[, "t value"]), lower.tail = FALSE) * 2
ctable_6 <- cbind(ctable_6, "p value" = p)
# interaction not needed

# check org*edu
m7 <- polr(L3_2 ~ factor(org_cat)*factor(edu_cat) + factor(gen_d) + factor(over_d) , data =
L3data, Hess=TRUE)
summary(m7)
ctable_7 <- coef(summary(m7))
p <- pnorm(abs(ctable_7[, "t value"]), lower.tail = FALSE) * 2
ctable_7 <- cbind(ctable_7, "p value" = p)
# interaction not needed
```

```
# check org*overdose
m8 <- polr(L3_2 ~ factor(org_cat)*factor(over_d) + factor(edu_cat) + factor(gen_d), data =
L3data, Hess=TRUE)
summary(m8)
ctable_8 <- coef(summary(m8))
p <- pnorm(abs(ctable_8[, "t value"]), lower.tail = FALSE) * 2
ctable_8 <- cbind(ctable_8, "p value" = p)
# interaction not needed

# MODEL 1 IS STILL BEST
# check collinearity for best model (m1)
vif(m1)
# odds ratios for model 1, best final model
(ci_m1 <- confint(m1))
(exp(cbind(OR = coef(m1), ci_m1)))


## L7
# initial model based on univariates
m1 <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(exp_cat)+
factor(over_d), data = L7data, Hess=TRUE)
summary(m1)
ctable_1 <- coef(summary(m1))
p <- pnorm(abs(ctable_1[, "t value"]), lower.tail = FALSE) * 2
(ctable_1 <- cbind(ctable_1, "p value" = p))

# check overdose is needed
m2 <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(exp_cat), data =
L7data, Hess=TRUE)
summary(m2)
ctable_2 <- coef(summary(m2))
p <- pnorm(abs(ctable_2[, "t value"]), lower.tail = FALSE) * 2
(ctable_2 <- cbind(ctable_2, "p value" = p))
# should remove overdose, not significant, not confounding

# check experience is needed
m3 <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat),data = L7data, Hess=TRUE)
summary(m3)
ctable_3 <- coef(summary(m3))
p <- pnorm(abs(ctable_3[, "t value"]), lower.tail = FALSE) * 2
(ctable_3 <- cbind(ctable_3, "p value" = p))
# Experience is not sig. but is a confounder for organization

# check gender is needed
m4 <- polr(L7_2 ~ factor(org_cat)+ factor(edu_cat) + factor(exp_cat),data = L7data, Hess=TRUE)
summary(m4)
```

```
ctable_4 <- coef(summary(m4))
p <- pnorm(abs(ctable_4[, "t value"]), lower.tail = FALSE) * 2
(ctable_4 <- cbind(ctable_4, "p value" = p))
# should keep gender, significant

# check education is needed
m5 <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(exp_cat),data = L7data, Hess=TRUE)
summary(m5)
ctable_5 <- coef(summary(m5))
p <- pnorm(abs(ctable_5[, "t value"]), lower.tail = FALSE) * 2
(ctable_5 <- cbind(ctable_5, "p value" = p))
# should keep education, significant

# check org is needed
m6 <- polr(L7_2 ~ factor(gen_d) + factor(edu_cat) + factor(exp_cat), data = L7data, Hess=TRUE)
summary(m6)
ctable_6 <- coef(summary(m6))
p <- pnorm(abs(ctable_6[, "t value"]), lower.tail = FALSE) * 2
(ctable_6 <- cbind(ctable_6, "p value" = p))
# should keep org, significant

## Add back in unused vars
# check region is needed
m3_3  <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) +factor(exp_cat) +
factor(reg_d), data = L7data, Hess=TRUE)
summary(m3_3)
ctable_3_3 <- coef(summary(m3_3))
p <- pnorm(abs(ctable_3_3[, "t value"]), lower.tail = FALSE) * 2
(ctable_3_3 <- cbind(ctable_3_3, "p value" = p))
# reg not needed, not confounding

# check race is needed
m3_4 <- polr(L7_2 ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) +
         factor(exp_cat) + factor(race_d), data = L7data, Hess=TRUE)
summary(m3_4)
ctable_3_4 <- coef(summary(m3_4))
p <- pnorm(abs(ctable_3_4[, "t value"]), lower.tail = FALSE) * 2
(ctable_3_4 <- cbind(ctable_3_4, "p value" = p))
# race not needed, not confounding

## Check Interactions
# check org*gen
m7 <- polr(L7_2 ~ factor(org_cat)*factor(gen_d) + factor(edu_cat) +
        factor(exp_cat), data = L7data, Hess=TRUE)
summary(m7)
ctable_7 <- coef(summary(m7))
```

```
p <- pnorm(abs(ctable_7[, "t value"]), lower.tail = FALSE) * 2
ctable_7 <- cbind(ctable_7, "p value" = p)
# interaction not needed

# check org*edu
m8 <- polr(L7_2 ~ factor(org_cat)*factor(edu_cat) + factor(gen_d) +
        factor(exp_cat), data = L7data, Hess=TRUE)
summary(m8)
ctable_8 <- coef(summary(m8))
p <- pnorm(abs(ctable_8[, "t value"]), lower.tail = FALSE) * 2
ctable_8 <- cbind(ctable_8, "p value" = p)
# interaction not needed

# check org*exp
m9 <- polr(L7_2 ~ factor(org_cat)*factor(exp_cat) + factor(gen_d) +
        factor(edu_cat), data = L7data, Hess=TRUE)
summary(m9)
ctable_9 <- coef(summary(m9))
p <- pnorm(abs(ctable_9[, "t value"]), lower.tail = FALSE) * 2
ctable_9 <- cbind(ctable_9, "p value" = p)
# interaction not needed

# MODEL 2 IS BEST MODEL
# check collinearity for best model, model 2
vif(m2)
# odds ratios for model 2
(ci_m2 <- confint(m2))
(exp(cbind(OR = coef(m2), ci_m2)))
```

Appendix A.2.5 Proportional Odds Assumption

```
## L1
L1data$Organization <- as.factor(L1data$org_cat)
L1data$Gender <- as.factor(L1data$gen_d)
L1data$Experience <- as.factor(L1data$exp_cat)
L1data$Overdoses <- as.factor(L1data$over_d)
L1data$Region <- as.factor(L1data$reg_d)
# create graphical check method
# qlogis transforms a probability to a logit
sf <- function(y) {
 c('Y>=1' = qlogis(mean(y >= 0)),
   'Y>=1' = qlogis(mean(y >= 1)),
   'Y>=2' = qlogis(mean(y >= 2)),
   'Y>=3' = qlogis(mean(y >= 3)))
```

```
}

(s <- with(L1data, summary(as.numeric(L1_2) ~ Organization*Region + Gender + Experience +
Overdoses, fun=sf)))

s[, 5] <- s[, 5] - s[, 4]
s[, 4] <- s[, 4] - s[, 4]
s[, 3] <- s[, 3] - s[, 3]
s # print
# graph
plot(s, which=1:4, pch=1:4, xlab='logit', main=' ', xlim=range(s[,4:5]))

#Logistic regression L1
# create binary outcome for logistic, agree 0 vs disagree 1
L1data$L1_b <- case_when(sju$L1_2=="1" ~ '0',
                 sju$L1_2=="2" ~ '0',
                 sju$L1_2=="3" ~ '1',
                 TRUE ~ '0')

# regression
L1_log <- glm(factor(L1_b) ~ factor(org_cat) + factor(gen_d) + factor(exp_cat) + factor(over_d)
+ factor(reg_d), data = L1data, family = "binomial")
summary(L1_log)
(ci_1log <- confint(L1_log))

# odds ratios for model 1 log
(exp(cbind(OR = coef(L1_log), ci_1log)))


## L3
L3data$Organization <- as.factor(L3data$org_cat)
L3data$Gender <- as.factor(L3data$gen_d)
L3data$Overdose <- as.factor(L3data$over_d)
L3data$Education <- as.factor(L3data$edu_cat)

# create graphical check method
# qlogis transforms a probability to a logit
sf <- function(y) {
  c('Y>=1' = qlogis(mean(y >= 0)),
   'Y>=1' = qlogis(mean(y >= 1)),
   'Y>=2' = qlogis(mean(y >= 2)),
   'Y>=3' = qlogis(mean(y >= 3)))
}

(s <- with(L3data, summary(as.numeric(L3_2) ~ Organization + Gender + Education + Overdose,
fun=sf)))
```

```
s[, 5] <- s[, 5] - s[, 4]
s[, 4] <- s[, 4] - s[, 4]
s[, 3] <- s[, 3] - s[, 3]
s # print
plot(s, which=1:4, pch=1:4, xlab='logit', main=' ', xlim=range(s[,4:5]))

#Logistic regression L3
# create binary outcome for logistic, agree 0 vs disagree 1
L3data$L3_b <- case_when(sju$L3_2=="1" ~ '0',
                 sju$L3_2=="2" ~ '0',
                 sju$L3_2=="3" ~ '1',
                 TRUE ~ '0')

# test logistic
L3_log <- glm(factor(L3_b) ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(over_d),
data = L3data, family = "binomial")
summary(L3_log)
(ci_3log <- confint(L3_log))

# odds ratios for model 2
(exp(cbind(OR = coef(L3_log), ci_3log)))


## L7
L7data$Organization <- as.factor(L7data$org_cat)
L7data$Gender <- as.factor(L7data$gen_d)
L7data$Experience <- as.factor(L7data$exp_cat)
L7data$Education <- as.factor(L7data$edu_cat)

# create graphical check method
# qlogis transforms a probability to a logit
sf <- function(y) {
  c('Y>=1' = qlogis(mean(y >= 0)),
   'Y>=1' = qlogis(mean(y >= 1)),
   'Y>=2' = qlogis(mean(y >= 2)),
   'Y>=3' = qlogis(mean(y >= 3)))
}

(s <- with(L7data, summary(as.numeric(L7_2) ~ Organization + Gender + Education +
Experience, fun=sf)))

s[, 5] <- s[, 5] - s[, 4]
s[, 4] <- s[, 4] - s[, 4]
s[, 3] <- s[, 3] - s[, 3]
s # print
#graph
```

```
plot(s, which=1:4, pch=1:4, xlab='logit', main=' ', xlim=range(s[,4:5]))

#Logistic regression L7
# create binary outcome for logistic, agree 0 vs disagree 1
L7data$L7_b <- case_when(sju$L7_2=="1" ~ '0',
                sju$L7_2=="2" ~ '0',
                sju$L7_2=="3" ~ '1',
                TRUE ~ '0')

# test logistic
L7_log <- glm(factor(L7_b) ~ factor(org_cat) + factor(gen_d) + factor(edu_cat) + factor(exp_cat),
data = L7data, family = "binomial")
summary(L7_log)
(ci_7log <- confint(L7_log))

# odds ratios for model 2
(exp(cbind(OR = coef(L7_log), ci_7log)))
```

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