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Modeling Employee Burnout and Stress Levels Using Generalized Linear Models

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MODELING EMPLOYEE BURNOUT AND STRESS LEVELS USING GENERALIZED LINEAR MODELS

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Abstract

In recent years, mental health has become a more prominent problem worldwide. One specific area of rising concern is the increase in the amount of stress and burnout that many people are experiencing. This research seeks to investigate the factors that are affecting stress and burnout as they pertain to the workplace environment. A series of multinomial logistic regression models and Poisson regression models are used to identify the factors affecting employees' stress and burnout with respect to the workplace environment using the most recent Work, Family, and Health Study (WFHS) dataset from the Work, Family, and Health Network. This research found that important factors affecting stress and burnout include decision authority, job demands, and job satisfaction.

Introduction

Mental health has been a rising concern worldwide, as evidenced by the 13% increase in the incidence of mental health conditions within the past decade, according to the World Health Organization (n.d.). Additionally, the National Institute of Mental Health estimates that approximately one in five U.S. adults was living with some kind of mental illness in 2021 (n.d.). Stress and burnout at work have also been on the rise in recent years, and according to the American Institute of Stress (2019), 83% of employees in the United States suffer from work-related stress. These alarming statistics speak to the need for a better understanding of the causes of employee stress and burnout in order to improve mental health outcomes.

One area that has been heavily researched is the relationship between work and employee stress. This area of research is important for both employees' personal health and well-being and for their employers' overall success, as poor mental health can result in absenteeism, decreased work performance, bad attitudes and behaviors, and poor work relationships (Harnois et al., 2000). Because of these negative outcomes, many have begun to research what factors influence employee burnout and stress.

Christina Maslach and colleagues (2001) explain that some possible causes of burnout might include high job demands, a lack of autonomy, the absence of job resources, and individual factors such as personality characteristics and job attitudes. A case study in the UK came to similar conclusions, citing that a loss of control and feelings of powerlessness also contribute to employee stress (Harnois et al., 2000). Another source found sufficient findings in the literature that show the great impact that job satisfaction can have on workplace burnout (Friganović et al., 2019). Finally, another paper looked specifically at the difference between job stress and job burnout and discovered that they seem to be highly correlated with slightly different factors. Factors related to job strain were more highly correlated to stress, whereas burnout was more correlated with variables such as job dissatisfaction, a desire to quit, and emotions regarding perceived performance (Pines and Kinan, 2005).

This paper will focus on one particular study, the Work, Family, and Health Study (WFHS), which was led by the Work, Family, and Health Network (2018). This study was created to better understand how different workplace practices and policies influence employees' work, family lives, and overall health and well-being. Many researchers have already used this dataset to gain a better understanding of the employee experience and how different factors can affect employees' overall health and well-being. For example, using general linear models on the WFHS dataset, Lawson, Lee, and Maric (2021) focused on work-to-family conflict and how it could influence physical and mental health, discovering that increased conflict seems to be correlated with individuals who report poorer sleep and higher psychological distress. Fan et al. (2019) used group-based multitrajectory modeling on the WFHS dataset and found that workers in higher-strain environments have much worse long-term well-being outcomes than those in lower-strain environments. Vigoureux et al. (2020) have included stress as a predictor variable rather than a response variable in multilevel models to examine the relationship between sleep quantity and perceptions of stress. The researchers discovered that higher stress levels are strongly related to poorer metabolic health outcomes, showing that stress levels negatively affect employees' mental and physical health.

Overall, much research has been done investigating employee burnout and stress. Many publications have been written on the analysis of the WFHS, but few have focused solely on understanding the factors that influence employee stress and burnout. This paper seeks to fill this gap and investigate the factors that affect employee stress and burnout by using the previously mentioned publicly accessible WFHS dataset.

About the Dataset

The WFHS data were gathered through randomized field experiments that assessed individuals in the information technology department of a Fortune 500 company (Work, Family and Health Network, 2018). Each participant in the study was asked a series of questions on topics such as the number of hours they work, how flexible their job is, what their work-life balance is like, how satisfying their job is, and how stressed and burned out their job makes them feel (Work, Family and Health Network, 2018). Two important variables to note in the WFHS dataset that will be explored throughout the remainder of this paper are the variables Psychological Distress and Emotional Burnout.

Psychological Distress

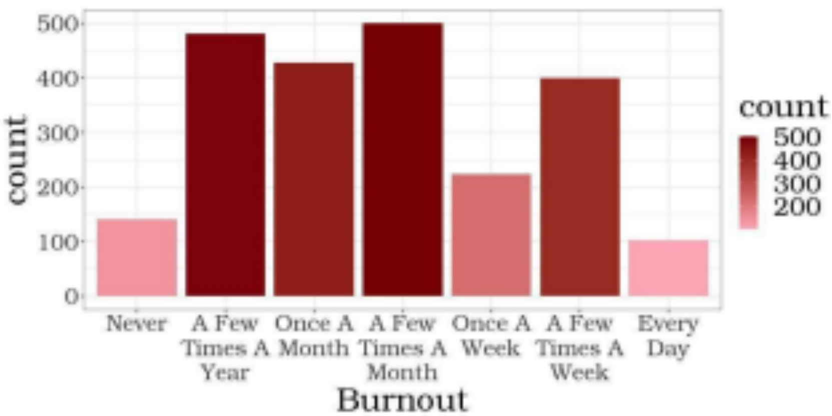
The first variable that this research focuses on is Psychological Distress. The measure used by the WFHS to quantify Psychological Distress is known as K6 and will be discussed in greater detail later in this paper. The distribution for this variable is shown in Figure 1. As can be seen in Figure 1, most respondents' stress levels fell between 7 and 11, indicating that they fell within the range of low mental stress; however, it is also apparent that a fair number of respondents had scores ranging from 12 to 19, falling into the category of moderate mental stress, and a few fell into the category of severe psychological distress.

Figure 1. Psychological Stress Variable Distribution

Employee Burnout

The second variable that this research will focus on is Burnout. This is a categorical variable that corresponds to the survey question "You feel burned out by your work. How often do you feel this way?" (Work, Family and Health Network, 2018). The bar chart in Figure 2 shows the frequency of different responses to this question. In this chart, it appears that most respondents fell into the category of feeling burnout a few times a year to a few times a month. Quite a few people also answered that they felt burned out a few times a week; however, it's important to note that there were fewer responses for the extremes of never or always feeling burned out.

Figure 2. Frequency of Respondent Burnout



Kessler 6 Psychological Distress Metric

The Kessler 6, or K6, is the measure used to evaluate the level of psychological distress of each employee. According to the WFHS (Work, Family and Health Network, 2018), "K6 is the most widely used mental health screening scale in the United States and has been used in numerous psychiatric and social epidemiology studies, including the National Household Survey on Drug Abuse." The K6 metric is constructed by taking the sum of a respondent's answers to six questions. These questions revolve around how often the respondent feels "nervous," "hopeless," "restless or fidgety," "so depressed that nothing could cheer you up," "that everything was an effort," and "worthless" (Kim et al., 2016). The result is a discrete score ranging from 6 to 30. A score of 6 indicates that a respondent reported never feeling any of these feelings, and a 30 indicates that the respondent always felt each of these feelings.

It is easiest to understand the K6 scores in terms of low, medium, and high stress. According to Prochaska (2012), a score between 5 and 13 on a K6 scale ranging from 0 to 24 indicates moderate mental stress, and a score greater than 13 indicates severe psychological distress. When adjusting this to the K6 scale used in this study (from 6 to 30), the cutoff points become 11 (5 + 6) for moderate mental stress and 19

(13 + 6) for severe psychological distress. Table 1 shows these cutoff points for psychological distress.

Table 1. K6 Scores and Interpretations

Kessler 6	
Score	**Psychological Distress Level**
6	No Psychological Distress
7-11	Low Psychological Distress
12-19	Moderate Psychological Distress
20-30	High Psychological Distress

Objective

The main objective of this research is to use the WFHS study data to identify how workplace practices and policies influence employee stress and burnout. The main objective will be achieved in two parts, by identifying the factors that affect employee stress and identifying the factors that affect employee burnout.

Methodology

Because of the types of response variables, we need two types of models to determine which factors are affecting employee burnout and employee stress. The response variable of the first model, Employee Stress, takes a discrete value between 6 and 30. Poisson random variables are frequently used to model counts with a minimum value of 0 and a maximum value that is unbounded (in theory) (Roback and Legler, 2021). Because Poisson regression predicts responses for count data, it is a good choice for modeling the Employee Stress response variable.

The response variable of the second model is Employee Burnout. This is a categorical variable that takes the values *Never*, *A few times a year*, *Once a month*, *A few times a month*, *Once a week*, *A few times a week*, and *Every day*. Multinomial logistic regression is used to model variables with a finite number of categorical outcomes. It does this by modeling the log odds of the outcomes in relation to a linear combination of predictor variables (UCLA: Statistical Consulting Group, 2021a, 2021b). Because multinomial logistic regression can be used to classify variables with a set number of categorical responses, this is therefore a good fit for the Emotional Burnout response variable, which takes only one of seven possible values.

Poisson Regression

Poisson regression is an instance of the generalized linear model that is used when the response variable Y is a random variable that takes nonnegative integer values (Penn State: Eberly College of Science, 2016). Let Y be a Poisson random variable with mean λ. Connecting the mean of the Poisson response variable and the linear combination of $x_1, \dots, x_k$ predictor variables using logarithm link function, the Poisson regression model can be written as

$$\ln(\lambda) = \beta_0 + x_1\beta_1 + x_2\beta_2 + \dots + x_k\beta_k \quad .$$

Then, by solving for λ, we have the equivalent expression

$$\lambda = \exp(\beta_0 + x_1\beta_2 + x_2\beta_2 + \dots + x_k\beta_k) \quad .$$

The model coefficients, $\beta_1, \dots, \beta_k$, can be interpreted in the following way: A one-unit increase in the predictor variable x_i changes the log of the response variable by β_i units when all other predictor variables remain fixed.

Multinomial Logistic Regression

Because the response variable Emotional Burnout is a multiclass response variable, we use a multinomial logistic regression model. The multinomial logistic regression handles multiple classes, in comparison to the two classes handled similarly by the logistic regression model (Cheng et al., 2021). The multinomial logistic regression model reserves one response category as the *base* case and maps the log odds of other response categories compared to the *base* case category. Let the *base* case response category be denoted as $Y = y_0$ and the remaining categories be denoted as $Y = y_1, \dots, y_m$. Then the multinomial regression model looks like

$$log(P(Y = y_i) \,/\, P(Y = y_0)) = \beta_{0i} + x_1\beta_{1i} + x_2\beta_{2i} + \dots + x_k\beta_{ki} \ ,$$

where $y_i = y_1, y_2, \dots, y_m$.

The model coefficients can be interpreted in the following way: When x_i increases by one unit, the log odds of response variable category (y_i) relative to the base case (y_0) would be expected to change by β_i units while keeping all other predictor variables fixed.

Data Preprocessing

Prior to modeling, some data preprocessing had to be performed to clean the data and make them usable for the chosen models. The first thing as a part of the preprocessing was to relabel to make the data easier to interpret quickly. For example, the variables were given new meaningful names that corresponded to the survey questions. In addition to this relabeling, the responses were recoded from their numerical form back into their original survey response answers. For example, if a variable had the value 1, we converted this back to *strongly agree* or *every day*, depending on the written response corresponding to that numeric value for the given question. After the data were relabeled, observations with missing values had to be removed because the machine learning algorithms that we selected do not perform well on data with missing values. Prior to the removal of observations with missing values, there were 3,684 observations, and after their removal, there were 2,794 observations. Another component of data preprocessing that we performed prior to modeling was outlier analysis. Other than missing values, however, no outliers were removed, because all data contained valid responses to the survey questions and we did not want to risk removing data that might give insights into important trends.

We then performed a multicollinearity analysis between the predictor variables to evaluate a standard regression assumption of no multicollinearity between independent variables. When a pair of predictor variables had a correlation coefficient greater than 0.5, one was removed after they were carefully analyzed. Then the principal component analysis (PCA) allowed us to reduce the number of predictor variables included in the regression models. The original goal was to include only the variables that directly corresponded to the survey response data, rather than the constructed variables that were the mean of these responses for each category. When the original variables were used, however, there were complications with building the models because many of the variables took similar values, resulting in infeasible model solutions. We therefore decided to focus only on the constructed quantitative variables given in the dataset.

The original dataset contained 21 quantitative variables. After a few of these attributes were removed because of multicollinearity, each model contained 18 attributes, making PCA no longer necessary. Table 2 shows the selected quantitative variables at the end of data preprocessing.

Table 2. Attributes Selected for Modeling

Attribute	Employee Stress	Employee Burnout
ActualWeeklyHours	X	X
DecisionAuthority	X	X
EmotionalBurnout	X	
ExpectedWeeklyHours	X	X
FamilyToWorkConflict	X	X
JobDemands	X	X
JobSatisfaction		X
LikelyToQuit	X	X
LowValueWork	X	X
NumberHoursInBed	X	X
OrganizationalCitizenship	X	X
PerceivedStress	X	X
PositiveWorkToFamily	X	X
RatePerformanceOthers	X	X
RatePerformanceSelf	X	X
SupervisorFamilySupport	X	X
TimeAdequacy	X	X
WorkFamilyIssues	X	X
WorkHours	X	X

Results

Identifying Factors that Affect Employee Stress

The first objective of this paper is to determine the factors affecting employee stress. The response variable, in this case, is Psychological Distress. This discrete variable identifies the Kessler 6 psychological distress score for each individual. This variable ranges from 6 to 29. Because this variable is a discrete count, a Poisson regression model works well. After removing the variables that cause multicollinearity within the dataset, the model is as shown below:

$$\log(AvgPsychologicalDistress) = \beta_0 + \beta_1 FamilyToWorkConflict + \beta_2 NumberHoursInBed + \beta_3 PositiveWorkToFamily + \beta_4 RatePerformance\ Others + \beta_5 PerceivedStress + \beta_6 WorkHours + \beta_7 RatePerformanceSelf +$$

$$\beta_8 \textit{OrganizationalCitizenship} + \beta_9 \textit{LikelyToQuit} + \beta_{10} \textit{ExpectedWeekly Hours} + \beta_{11} \textit{SupervisorFamilySupport} + \beta_{12} \textit{ActualWeeklyHours} + \beta_{13} \textit{Job Demands} + \beta_{14} \textit{DecisionAuthority} + \beta_{15} \textit{WorkFamilyIssues} + \beta_{16} \textit{LowValueWork} + \beta_{17} \textit{EmotionalBurnout} + \beta_{18} \textit{TimeAdequacy}$$

After running this model, we evaluated the 95% confidence intervals for the coefficient estimate for each variable in the model. The 95% confidence intervals of the parameter estimate of the variables PerceivedStress, OrganizationalCitizenship, DecisionAuthority, and EmotionalBurnout did not contain zero in them, thus making them significant factors in the model. Table 3 shows all model coefficient estimates and confidence intervals.

Table 3. Psychological Distress Model Outputs

Coefficients	**Estimate**	**2.5%**	**97.5%**
(Intercept) *	**1.653**	**1.3475**	**1.9581**
ActualWeeklyHours	0.0008	-0.0006	0.0023
DecisionAuthority *	**-0.0244**	**-0.047**	**-0.0017**
EmotionalBurnout *	**0.0343**	**0.0227**	**0.0459**
ExpectedWeeklyHours	-0.0005	-0.0036	0.0026
FamilyToWorkConflict	0.0139	-0.0076	0.0354
JobDemands	-0.0207	-0.0428	0.0015
LikelyToQuit	0.0072	-0.0067	0.0211
LowValueWork	-0.0143	-0.0298	0.0013
NumberHoursInBed	0.0037	-0.0099	0.0174
OrganizationalCitizenship *	**0.0404**	**0.0164**	**0.0644**
PerceivedStress *	**0.066**	**0.0604**	**0.0717**
PositiveWorkToFamily	0.0125	-0.0102	0.0353
RatePerformanceOthers	0.0009	-0.0123	0.0142
RatePerformanceSelf	-0.0034	-0.0172	0.0104
SupervisorFamilySupport	0.0035	-0.0147	0.0217
TimeAdequacy	-0.0154	-0.041	0.0103
WorkFamilyIssues	-0.0085	-0.0264	0.0095
WorkHours	-0.0037	-0.0279	0.0204

Based on the parameter estimates, for PerceivedStress, a one-unit increase in PerceivedStress increases the log of PsychologicalDistress by 0.66 when all other predictor variables remain constant. For OrganizationalCitizenship, a one-unit increase in OrganizationalCitizenship increases the log of PsychologicalDistress by 0.0404 when all other predictor variables remain constant. For DecisionAuthority, a one-unit increase in DecisionAuthority decreases the log of PsychologicalDistress by 0.0244 when all other predictor variables remain constant. Finally, for EmotionalBurnout, a one-unit increase in EmotionalBurnout increases the log of PsychologicalDistress by 0.0343 when all other predictor variables remain constant.

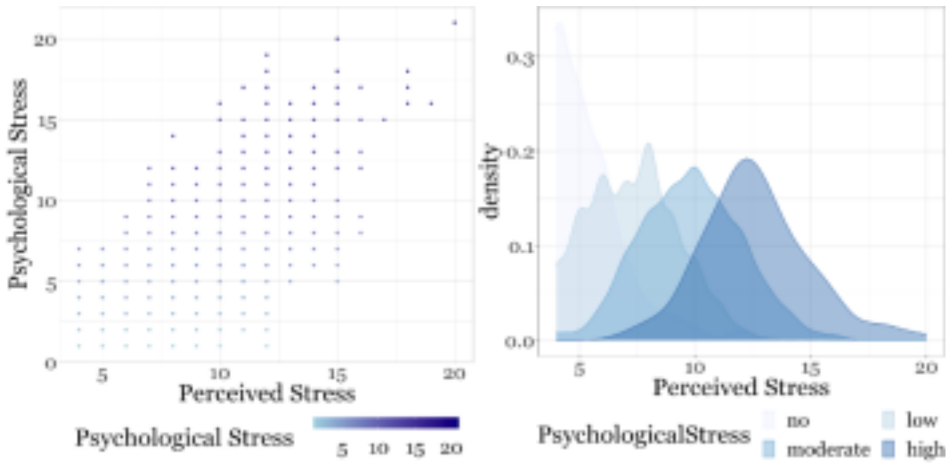
Each of the significant variables mentioned above will be explored in greater detail in their own subsections. Each subsection references survey questions from the WFHS (Work, Family and Health Network, 2018).

Perceived Stress

The variable PerceivedStress refers to the sum of a respondent's answers to four questions: (1) "During the past 30 days, how often have you felt that you were unable to control the important things in your life?" (2) "During the past 30 days, how often have you felt confident about your ability to handle your personal problems?" (3) "During the past 30 days, how often have you felt that things were going your way?" (4) "During the past 30 days, how often have you felt difficulties were piling up so high that you could not overcome them?"

As shown in the scatterplot in Figure 3, there is a moderately strong linear relationship ($r = 0.7$) between Perceived Stress and Psychological Distress. This same trend is also shown by the density graph, which breaks psychological distress into the four levels as described above. It is apparent that those with no psychological distress also tend to have lower perceived stress, and those with high psychological distress tend to have high perceived stress.

Figure 3. Perceived Stress and Psychological Distress Scatterplot (left) and Density Plot (right)

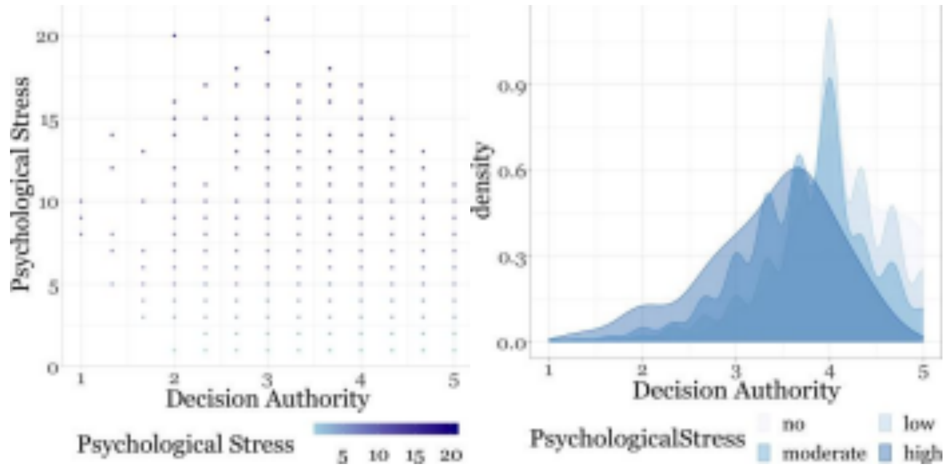


Decision Authority

The predictor variable Decision Authority is created by taking the mean of individual responses to three statements: (1) "Your job allows you to make a lot of decisions on your own." (2) "On your job, you have very little freedom to decide how you do your work." (3) "You have a lot of say about what happens on your job."

In the scatter plot in Figure 4, there appears to be a weak negative relationship between psychological distress and decision authority. This means that as decision authority increases (i.e., when an individual feels they have more freedom to control their work), they have lower psychological distress. This same trend can be shown in the density plot, where it appears that those who have high psychological stress have lower median decision authority, and those with lower psychological stress have higher decision authority.

Figure 4. Decision Authority and Psychological Distress Scatterplot (left) and Density Plot (right)

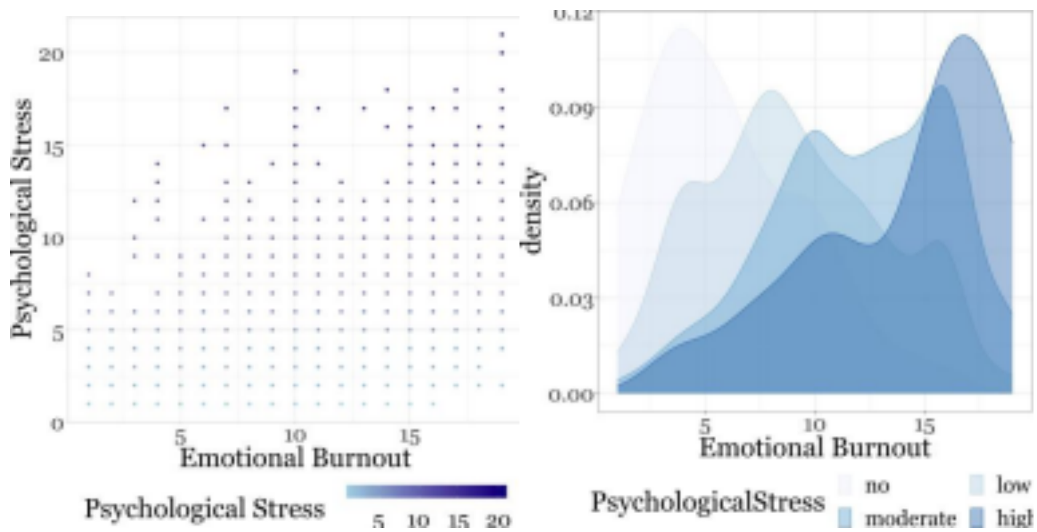


Emotional Burnout

Emotional Burnout is a different variable than the categorical response variable BurnedOut, which is discussed in the next section. Emotional Burnout is the mean of the respondents' answers to the following questions, which do include the other response variable BurnedOut. The respondents were asked to answer three questions: (1) "You feel emotionally drained from your work. How often do you feel this way?" (2) "You feel burned out by your work. How often do you feel this way?" (3) "You feel used up at the end of the workday. How often do you feel this way?"

In the scatterplot in Figure 5, there appears to be a slightly positive relationship between employee burnout and psychological distress. This indicates that as feelings of emotional burnout increase, so do feelings of psychological distress. This is also much more clearly seen on the density plot, where those with high psychological stress have a much higher burnout compared to those with no or low psychological distress.

Figure 5. Emotional Burnout and Psychological Distress Scatterplot (left) and Density Plot (right)



Additional Results

In addition to the variables described above, the variable OrganizationalCitizenship was also found to be statistically significant in the model for Psychological Distress. There appeared to be little to no correlation between Psychological Distress and OrganizationalCitizenship, however. This indicates that this might be an area for further research to understand better how organizational citizenship might affect psychological distress.

Identifying Factors That Affect Employee Burnout

The second objective of this paper is to determine the factors affecting employee burnout. The response variable in this case is BurnedOut. This categorical variable corresponds to the survey question "You feel burned out. How often do you feel this way?" (Work, Family and Health Network, 2018). The possible responses to this question include *Never*, *A few times a year*, *Once a month*, *A few times a month*, *Once a week*, *A few times a week*, and *Every day*. For this reason, multinomial logistic regression is a good model for the data.

Using the base case as y_0 = *Never*, the multinomial logistic regression model is as shown below:

$$log(P(Y = y_i) / P(Y = y_0)) = \beta_{0i} + x_1\beta_{1i} + x_2\beta_{2i} + \ldots + x_k\beta_{ki} ,$$

where $y_i = y_1, y_2, \ldots, y_m$,

where y_i = *A few times a year, Once a month, A few times a month, Once a week, A few times a week, Every day*

Here, β_{ki} are the coefficients for the regression model. These coefficients correspond to each of the variables in the model, which are also listed below:

SupervisorFamilySupport	FamilyToWorkConflict	PositiveWorkToFamily
OrganizationalCitizenship	LikelyToQuit	NumberHoursInBed
RatePerformanceOthers	PerceivedStress	ExpectedWeeklyHours
RatePerformanceSelf	ActualWeeklyHours	LowValueWork
TimeAdequacy	JobDemands	WorkHours
DecisionAuthority	JobSatisfaction	WorkFamilyIssues

After running this model, we evaluated the 95% confidence intervals for each coefficient estimate in the model. This output can be seen in Figures 6–11.

Figure 6. Log Odds of *A few times a year* Relative to *Never*

Predictors	**Estimate**	**2.50%**	**97.50%**
ActualWeeklyHours	-0.0017	-0.0256	0.0223
DecisionAuthority	0.1225	-0.2885	0.5334
ExpectedWeeklyHours	-0.0308	-0.0954	0.0337
FamilyToWorkConflict	0.1474	-0.2595	0.5543
JobDemands*	**0.6796**	**0.3288**	**1.0305**
JobSatisfaction	-0.4024	-0.8524	0.0475
LikelyToQuit	0.0042	-0.2565	0.265
LowValueWork	0.0481	-0.2106	0.3067
NumberHoursInBed	0.1413	-0.0704	0.3531
OrganizationalCitizenship*	**-0.4956**	**-0.8438**	**-0.1475**
PerceivedStress*	**0.1528**	**0.0496**	**0.256**
PositveWorkToFamily*	**0.544**	**0.2555**	**0.8326**
RatePerformanceOthers	0.0354	-0.1801	0.2508
RatePerformanceSelf*	**-0.2633**	**-0.5102**	**-0.0164**
SupervisorFamilySupport	-0.2312	-0.5679	0.1055
TimeAdequacy	0.2182	-0.1613	0.5977
WorkFamilyIssues	-0.0237	-0.2965	0.2492
WorkHours	0.3848	-0.0088	0.7783

Figure 7. Log Odds of *Once a month* Relative to *Never*

Predictors	Estimate	2.5%	97.5%
ActualWeeklyHours	-0.0008	-0.0254	0.0238
DecisionAuthority	-0.0008	-0.4216	0.4201
ExpectedWeeklyHours	-0.0149	-0.0794	0.0496
FamilyToWorkConflict*	**0.6002**	**0.1843**	**1.016**
JobDemands*	**0.9033**	**0.5366**	**1.2699**
JobSatisfaction*	**-0.6557**	**-1.1148**	**-0.1966**
LikelyToQuit	-0.004	-0.2711	0.2632
LowValueWork*	**0.2685**	**0.0042**	**0.5327**
NumberHoursInBed	0.1631	-0.0557	0.3819
OrganizationalCitizenship*	**-0.3695**	**0.101**	**0.7121**
PerceivedStress*	**0.2373**	**0.1323**	**0.3424**
PositveWorkToFamily*	**0.4065**	**0.101**	**0.7121**
RatePerformanceOthers	-0.0021	-0.2251	0.2209
RatePerformanceSelf	-0.2161	-0.4705	0.0383
SupervisorFamilySupport	-0.2478	-0.5901	0.0945
TimeAdequacy	0.1618	-0.2336	0.5572
WorkFamilyIssues	-0.1621	-0.4444	0.1202
WorkHours	0.3412	-0.0648	0.7471

Figure 8. Log Odds of *A few times a month* Relative to *Never*

Predictors	Estimate	2.5%	97.5%
ActualWeeklyHours	0.0172	-0.0082	0.0426
DecisionAuthority	-0.0241	-0.4516	0.4034
ExpectedWeeklyHours	-0.0112	-0.0749	0.0525
FamilyToWorkConflict	0.3903	-0.0307	0.8114
JobDemands*	**1.5494**	**1.1701**	**1.9286**
JobSatisfaction*	**-0.9778**	**-1.443**	**-0.5127**
LikelyToQuit	-0.0696	-0.3404	0.2012
LowValueWork*	**0.4362**	**0.168**	**0.7043**
NumberHoursInBed	0.0501	-0.171	0.2712
OrganizationalCitizenship*	**-0.4552**	**-0.8315**	**-0.0789**
PerceivedStress*	**0.3393**	**0.2329**	**0.4458**
PositiveWorkToFamily*	**0.6323**	**0.3091**	**0.9555**
RatePerformanceOthers	-0.0501	-0.2767	0.1765
RatePerformanceSelf*	**-0.3505**	**-0.6077**	**-0.0934**
SupervisorFamilySupport	-0.296	-0.6413	0.0493
TimeAdequacy	0.0065	-0.3966	0.4097
WorkFamilyIssues*	**-0.379**	**-0.6660**	**-0.092**
WorkHours	0.2373	-0.1761	0.6506

Figure 9. Log Odds of *Once a week* Relative to *Never*

Predictors	**Estimate**	**2.5%**	**97.5%**
ActualWeeklyHours	0.0251	-0.0035	0.0538
DecisionAuthority	-0.0563	-0.5245	0.4119
ExpectedWeeklyHours	0.0105	-0.0569	0.078
FamilyToWorkConflict*	**0.4731**	**0.0172**	**0.9289**
JobDemands*	**1.6823**	**1.2600**	**2.1047**
JobSatisfaction*	**-1.193**	**-1.6957**	**-0.6903**
LikelyToQuit	-0.0221	-0.3188	0.2746
LowValueWork*	**0.5417**	**0.2446**	**0.8388**
NumberHoursInBed	0.1577	-0.0911	0.4064
OrganizationalCitizenship*	**-0.4742**	**-0.9047**	**-0.0436**
PerceivedStress*	**0.3303**	**0.2139**	**0.4466**
PositiveWorkToFamily*	**0.7900**	**0.4061**	**1.1739**
RatePerformanceOthers	0.0295	-0.2244	0.2834
RatePerformanceSelf*	**-0.436**	**-0.7164**	**-0.1556**
SupervisorFamilySupport	-0.3272	-0.7028	0.0485
TimeAdequacy	-0.2137	-0.6665	0.2391
WorkFamilyIssues*	**-0.3718**	**-0.6955**	**-0.048**
WorkHours	0.1011	-0.3582	0.5605

Figure 10. Log Odds of *A few times a week* Relative to *Never*

Predictors	**Estimate**	**2.50%**	**97.50%**
ActualWeeklyHours	0.0174	-0.0097	0.0446
DecisionAuthority	-0.231	-0.6825	0.2204
ExpectedWeeklyHours	0.0092	-0.0561	0.0746
FamilyToWorkConflict*	**0.5358**	**0.0946**	**0.9769**
JobDemands*	**2.4948**	**2.0795**	**2.9101**
JobSatisfaction*	**-1.5565**	**-2.0454**	**-1.0676**
LikelyToQuit	0.032	-0.2542	0.3181
LowValueWork*	**0.3856**	**0.0986**	**0.6725**
NumberHoursInBed	0.0176	-0.2197	0.2549
OrganizationalCitizenship*	**-0.6496**	**-1.0643**	**-0.235**
PerceivedStress*	**0.386**	**0.2733**	**0.4987**
PositveWorkToFamily*	**0.5713**	**0.2112**	**0.9315**
RatePerformanceOthers	-0.0328	-0.2748	0.2092
RatePerformanceSelf*	**-0.3749**	**-0.6467**	**-0.103**
SupervisorFamilySupport*	**-0.373**	**-0.7368**	**-0.0091**
TimeAdequacy	-0.2776	-0.7177	0.1625
WorkFamilyIssues*	**-0.6492**	**-0.963**	**-0.3354**
WorkHours	0.283	-0.1609	0.7268

Figure 11. Log Odds of *Every day* Relative to *Never*

Predictors	**Estimate**	**2.50%**	**97.50%**
ActualWeeklyHours	0.0225	-0.0118	0.0568
DecisionAuthority*	**-0.5722**	**-1.1011**	**-0.0433**
ExpectedWeeklyHours	0.0264	-0.0474	0.1001
FamilyToWorkConflict	0.3709	-0.1568	0.8985
JobDemands*	**3.0772**	**2.536**	**3.6183**
JobSatisfaction*	**-1.9653**	**-2.5347**	**-1.396**
LikelyToQuit	0.004	-0.3458	0.3538
LowValueWork	0.3018	-0.0653	0.6689
NumberHoursInBed	0.0092	-0.297	0.3153
OrganizationalCitizenship*	**-0.069**	**-0.6263**	**-0.2028**
PerceivedStress*	**0.4997**	**0.3622**	**0.6373**
PositveWorkToFamily*	**0.6195**	**0.1181**	**1.1209**
RatePerformanceOthers	-0.0389	-0.3378	0.2601
RatePerformanceSelf*	**-0.502**	**-0.83**	**-0.1739**
SupervisorFamilySupport*	**-0.6351**	**-1.0674**	**-0.2028**
TimeAdequacy	-0.4906	-1.0742	0.093
WorkFamilyIssues*	**-0.6672**	**-1.088**	**-0.2464**
WorkHours	0.1019	-0.4647	0.6685

Our criterion for a predictor variable to be significant for a burnout frequency level (e.g., log odds of *A few times a year* relative to *Never*) follows: We will call a predictor variable for a burnout level significant if zero is not in the 95% confidence interval estimate for the predictor's corresponding β parameter.

Using this criterion, the predictor variables that are significant for at least one of the burnout frequency levels are FamilyToWorkConflict, JobDemands, JobSatisfaction, LowValueWork, OrganizationalCitizenship, PerceivedStress, PositiveWorkToFamily, RatePerformanceSelf, SupervisorFamilySupport, and WorkFamilyIssues. Figure 12 shows a summary of the significant results.

Figure 12. Summary of Employee Burnout Model Results

Log Odds Of…	Predictor Variable
A Few Times a Year Relative to Never	JobDemands
	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
	RatePerformanceSelf
Once a Month Relative to Never	FamilyToWorkConflict
	JobDemands
	JobSatisfaction
	LowValueWork
	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
A Few Times a Month Relative to Never	JobDemands
	JobSatisfaction
	LowValueWork
	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
	RatePerformanceSelf
	WorkFamilyIssues
Once a Week Relative to Never	FamilyToWorkConflict
	JobDemands
	JobSatisfaction
	LowValueWork
Once a Week Relative to Never Continued	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
	RatePerformanceSelf
	WorkFamilyIssues
A Few Times a Week Relative to Never	FamilyToWorkConflict
	JobDemands
	JobSatisfaction
	LowValueWork
	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
	RatePerformanceSelf
	SupervisorFamilySupport
	WorkFamilyIssues
Everyday Relative to Never	DecisionAuthority
	JobDemands
	JobSatisfaction
	OrganizationalCitizenship
	PerceivedStress
	PositiveWorkToFamily
	RatePerformanceSelf
	SupervisorFamilySupport
	WorkFamilyIssues

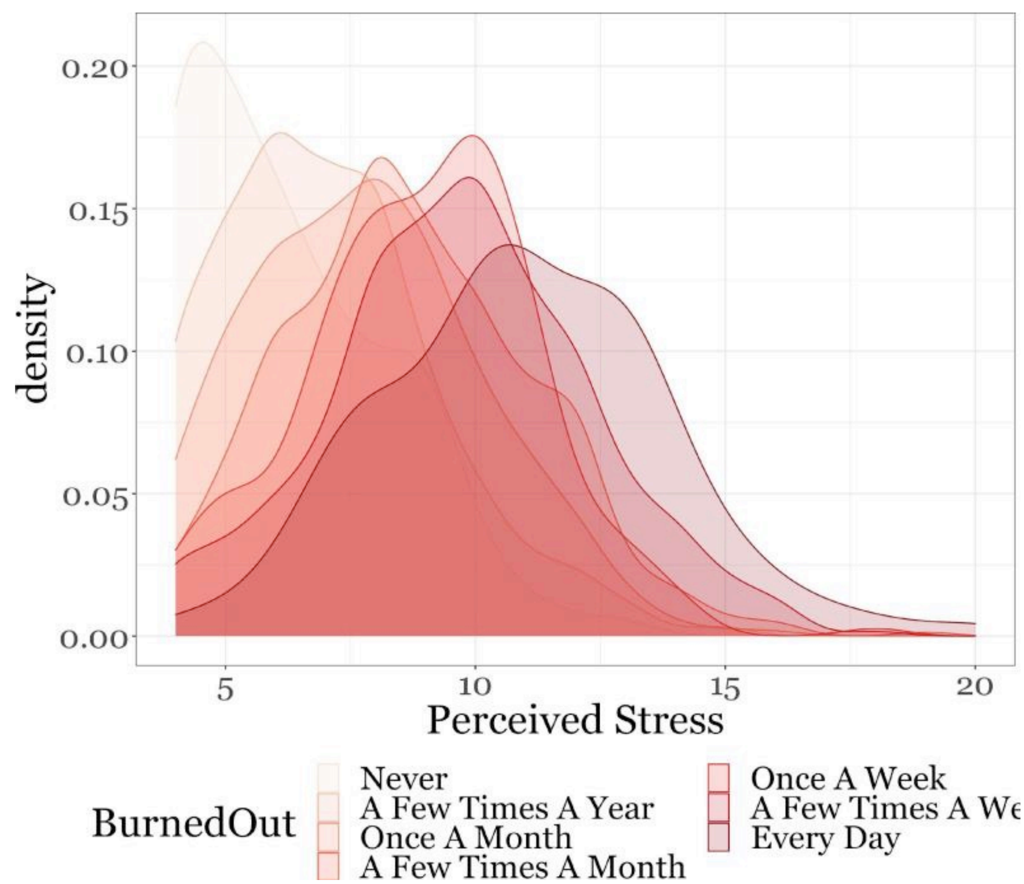
Following are a few examples of interpretations of some of the variables that are significant in the model. For PositiveWorkToFamily, when PositiveWorkToFamily increases by 1 unit, the log odds for *burned out a few times a year* relative to *never burned out* would be expected to increase by 0.544 while keeping all other variables constant. For FamilyToWorkConflict, when FamilyToWorkConflict increases by 1 unit, the log odds for *burned out once a month* relative to *never burned out* would be expected to increase by 0.6002 while keeping all other factors fixed. For OrganizationalCitizenship, when OrganizationalCitizenship increases by 1 unit, the log odds for *burned out every day* relative to *never burned out* would be expected to decrease by 0.069 while keeping all other factors fixed. All other coefficients can be interpreted similarly.

Now we will explore in greater detail each of the variables that was found to be significant in the model. Investigating these variables further leads to a greater understanding of how different work conditions and environments are related to emotional burnout.

Perceived Stress

Perceived Stress is the same predictor variable as described in the Psychological Distress section. In the density plot in Figure 13, we see a clear relationship between the variables BurnedOut and Perceived Stress. Those who never or rarely feel burned out seem to have much lower perceived stress as compared to those who feel burned out every day. This indicates that there is likely some kind of relationship between burnout experience and the quantity of perceived stress that someone feels.

Figure 13. Density Plot of Perceived Stress and BurnedOut

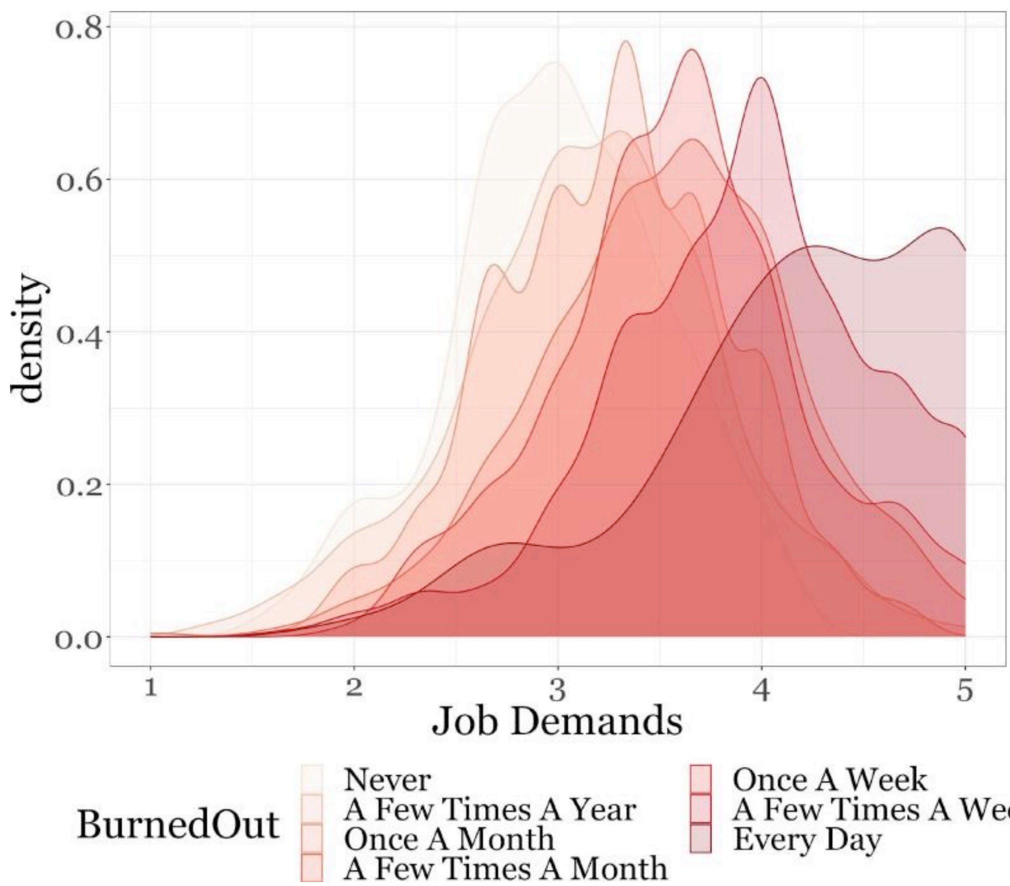


Job Demands

JobDemands is a predictor variable that corresponds to the mean of the respondents' responses to the following three statements: (1) "You do not have enough time to get your job done." (2) "Your job requires very fast work." (3) "Your job requires very hard work."

The density plot in Figure 14 again shows a clear relationship between the predictor variable of job demands and the response variable of feeling burned out. Those with lower burnout tend also to have lower job demands, and those with higher burnout tend to have higher job demands. This makes sense and could mean that decreasing job demands by ensuring employees have enough time to get their work done could lead to decreased burnout experience.

Figure 14. Density Plot for Job Demands and BurnedOut

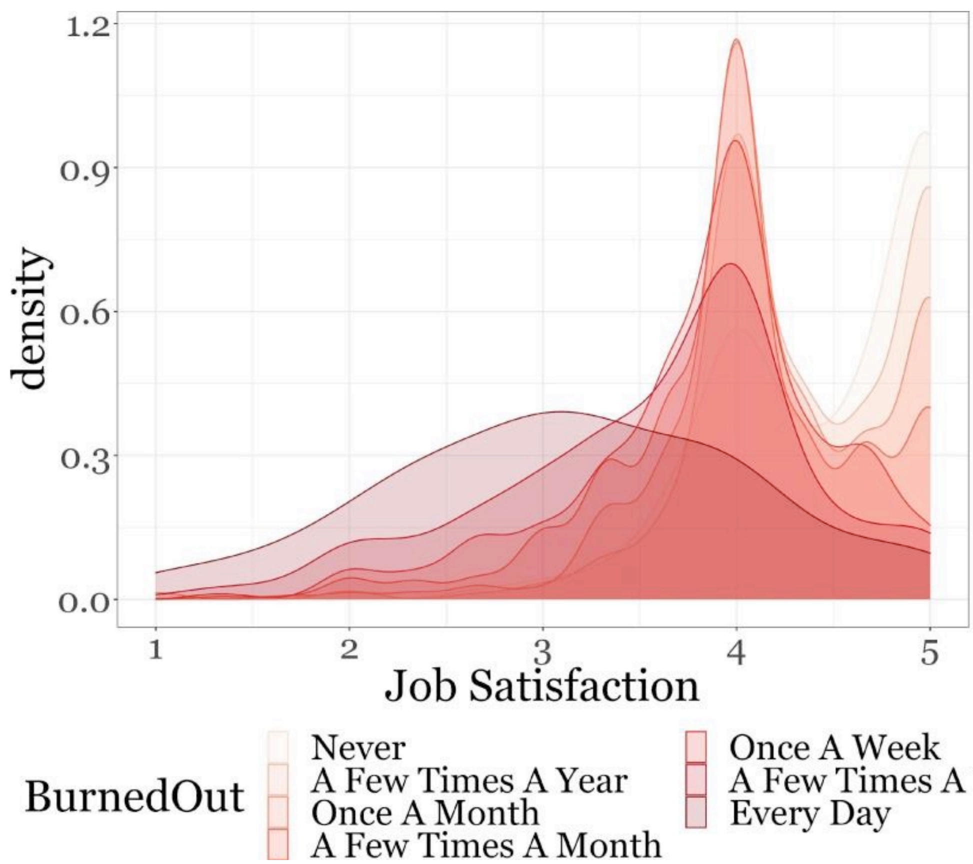


Job Satisfaction

The variable JobSatisfaction corresponds to the mean of the respondents' responses to the following statements: (1) "In general, you like working at your job." (2) "In general, you are satisfied with your job." (3) "You are generally satisfied with the kind of work you do in this job."

There appear to be a few key trends in the density plot in Figure 15. Those who experience burnout every day tend to have a much lower median level of job satisfaction, although there is also a much larger spread of job satisfaction for those who experience burnout every day. Another interesting thing to note is that those who never or rarely experience burnout have a much higher level of job satisfaction. This means if a company could determine how to help its employees achieve greater job satisfaction, the company could also potentially decrease how frequently employees feel burned out.

Figure 15. Density Plot for JobSatisfaction and BurnedOut

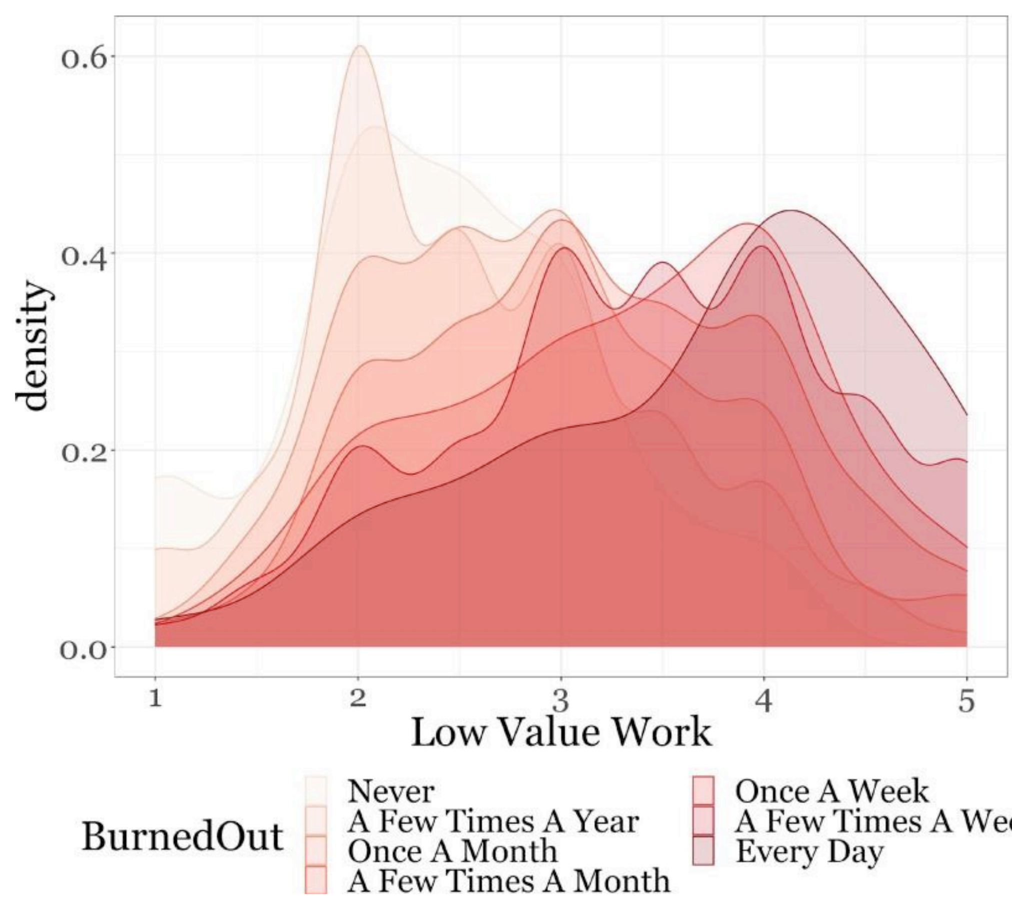


Low-Value Work

The variable LowValueWork corresponds to the mean of the responses to the following statements: (1) "You work on unnecessary things." (2) "You spend time in unproductive meetings."

The density plot in Figure 16 shows a clear trend that those who rate their work as having lower value (meaning they feel their time is frequently wasted) often also experience burnout more frequently, whereas those who do not feel like time is wasted tend to have a lesser frequency of experiencing burnout. This could lead to some simple solutions for employers. For example, one idea might be limiting meetings to only necessary ones and decreasing busy work to help decrease employee burnout.

Figure 16. Density Plot for LowValueWork and BurnedOut

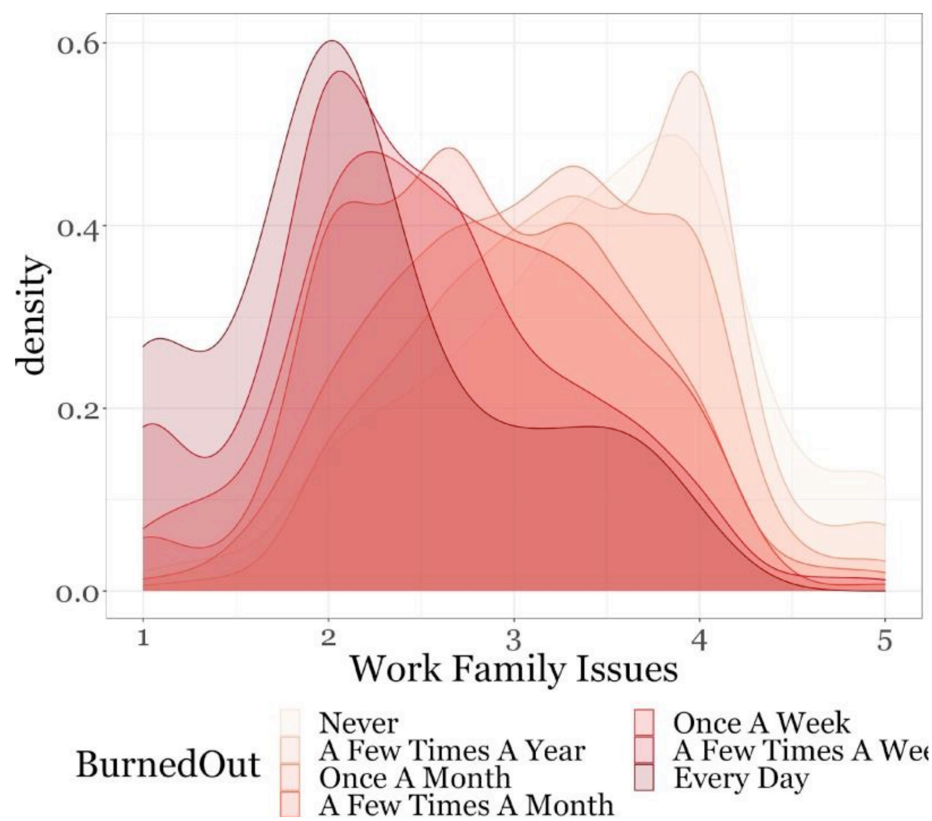


Work-Family Issues

The WorkFamilyIssues variable corresponds to the mean of the responses to the following three statements: (1) "In your workplace, employees are expected to take time away from their family or personal lives to get their work done." (2) "In your workplace, employees are expected to put their families or personal lives second to their jobs." (3) "In your workplace, employees are expected to make work their top priority."

The density plot in Figure 17 shows a few clear trends. For example, it shows that those with higher burnout experience tend to have lower work-family issues. Because this was a reverse-coded variable, this means that they feel as though work takes priority over their family or personal lives very frequently, whereas those who rarely or never experience burnout tend to have higher work-family-issue scores, indicating that they don't often feel that work must be their top priority over their family and personal lives.

Figure 17. Density Plot for WorkFamilyIssues and BurnedOut



Additional Findings

In addition to the results discussed above, a few other variables were found to be statistically significant within the employee burnout model at the 5% significance level. These variables were PositiveWorkToFamily, OrganizationalCitizenship, RatePerformanceSelf, FamilyToWorkConflict, and SupervisorFamilySupport. When visualizations were created and the relationship between these variables and emotional burnout were investigated, however, no obvious meaningful trends or patterns were found. This indicates that in the future it will be important to dive deeper into the correlation between these variables and burnout, as they could help provide more insight on what affects burnout.

Conclusion

This research sought to identify the factors affecting psychological distress and burnout using a Poisson regression model and a multinomial logistic regression model, respectively. In addition to the models discussed in this paper, various other models were also tested throughout this research. Because of the number of categorical variables in the dataset, we suspected that the model might involve random effects. To incorporate mixed effects in a multinomial setting, we first used the MCMCglmm package, which fits multivariate generalized linear mixed models using Markov chain Monte Carlo techniques (Hadfield, 2010). This was a significantly more complicated model, however, and did not find any random effects to be significant in the model, regardless of the variable selected as the random effects variable. For this reason, we used the simpler multinomial logistic regression model. We also explored mixed-effects Poisson regression for the psychological distress response variable; however, again, no random effects were found to be significant in the model. For this reason, the simpler Poisson regression model was selected.

The Poisson regression model for psychological distress concluded that PerceivedStress, OrganizationalCitizenship, DecisionAuthority, and EmotionalBurnout were significant based on coefficient estimates via 95% confidence intervals. The multinomial logistic regression model for emotional burnout concluded that PositiveWorktoFamily, OrganizationalCitizenship, PerceivedStress, JobDemands, RatePerformanceSelf, JobSatisfaction, LowValueWork, WorkFamilyIssues, FamilyToWorkConflict, and SupervisorFamilySupport were significant for at least one level of the multinomial values based on coefficient estimates via 95% confidence intervals.

An interesting finding is that the variables PerceivedStress and OrganizationalCitizenship were found to be significant in both the psychological distress model and emotional burnout model. This indicates that there is at least some overlap between the factors that affect stress and burnout. Additionally, emotional burnout and perceived stress were observed to be significant variables in determining (respectively) psychological distress and burnout; thus, there is a clear relationship between psychological stress and emotional burnout.

This information can be used to help employers create work environments where employee burnout and stress are minimized. Based on the significant factors, some actionable items for employers would be to ensure that employees' work is valued and that employers effectively use their employees' time, as this corresponds to the low-value-work factor. In addition, properly training managers to be supportive supervisors who understand and promote work-life balance pertains to the factors of work-family issues, family-to-work conflict, and supervisor family support. Finally, employers should ensure that they effectively balance the workloads assigned to employees, reducing unnecessary job demands and therefore hopefully reducing employee burnout and stress as well.

This research not only is beneficial for employers but can also be helpful for those looking to join the workforce or switch careers, as this gives insights on types of companies an individual might want to look for. First, they will want a job that brings them satisfaction, followed by a leader who will support their career growth and their work-life balance in a supportive community of workers.

Research on psychological distress and emotional burnout are useful topics and can further be extended into many other avenues. One such is cluster analysis, which uncovers natural groupings of the data, potentially revealing more relationships between different variables.

Finally, this research could also be expanded upon with examination of stress and burnout in different environments. For example, a similar study focused on college or high school students could help provide insights into how different learning environments and teachers or professors can affect student mental health. This research provides valuable insights into factors affecting employee stress and burnout and opens the door to future areas of investigation to help fight the ever-increasing mental health concerns in the world today.

References

American Institute of Stress. (2019, September 25). *42 worrying workplace stress statistics*. https://www.stress.org/42-worrying-workplace-stress-statistics

Cheng, H., Choi, Y., & Shi, Q. (2021, April 29). Multinomial logistic regression. In *Companion to BER 642: Advanced regression methods* (ch. 11). https://bookdown.org/chua/ber642 advanced regression/

Fan, W., Moen, P., Kelly, E. L., Hammer, L. B., & Berkman, L. F. (2019). Job strain, time strain, and well-being: A longitudinal, person-centered approach in two industries. *Journal of Vocational Behavior, 110*, 102–116.

Friganović, A., Selič, P., & Ilić, B. (2019). Stress and burnout syndrome and their association with coping and job satisfaction in critical care nurses: A literature review. *Psychiatria Danubina, 31*(suppl. 1), 21–31. https://hrcak.srce.hr/262691

Hadfield, J. D. (2010). MCMC methods for multi-response generalized linear mixed models: The MCMCglmm R package. *Journal of Statistical Software, 33*(2), 1–22.

Harnois, G., Gabriel, P., & World Health Organization International Labour Organisation. (2000). *Mental health and work: Impact, issues and good practices*. World Health Organization. https://aps.who.int/iris/handle/10665/42346

Kim, G., DeCoster, J., Bryant, A. N., & Ford, K. L. (2016). Measurement equivalence of the K6 scale: The effects of race/ethnicity and language. *Assessment, 23*(6), 758–768. https://doi.org/10.1177/1073191115599639

Lawson, K. M., Lee, S., & Maric, D. (2021). Not just work-to-family conflict, but how you react to it matters for physical and mental health. *Work & Stress, 35*(4), 327–343.

Maslach, C., Schaufeli W., & Leiter M. (2001). Job burnout. *Annual Review of Psychology, 52*(1), 397–422.

National Institute of Mental Health. (n.d.). *Mental illness.* U.S. Department of Health and Human Services. https://www.nimh.nih.gov/health/statistics/mental-illness

Penn State Eberly College of Science. (2016). *Logistic, Poisson & nonlinear regression*. Penn State University. https://newonlinecourses.science.psu.edu/stat501/node/369/

Pines, A., & Keinan, G. (2005). Stress and burnout: The significant difference. *Personality and Individual Differences, 39*(3), 625–635. https://doi.org/10.1016/j.paid.2005.02.009

Prochaska, J. J., Sung, H. Y., Max, W., Shi, Y., & Ong, M. (2012). Validity study of the K6 scale as a measure of moderate mental distress based on mental health treatment need and utilization. *International Journal of Methods in Psychiatric Research, 21*(2), 88–97. https://doi.org/10.1002/mpr.1349

Roback, P., & Legler, J. (2021*). Beyond multiple linear regression: Applied generalized linear models and multilevel models in R.* CRC Press.

UCLA: Statistical Consulting Group. (2021a). *Multinomial logistic regression—R data analysis examples.* UCLA Advanced Research Computing Statistical Methods and Data Analytics. stats.oarc.ucla.edu/r/dae/multinomial-logistic-regression/

UCLA: Statistical Consulting Group. (2021b). *Poisson regression—R data analysis examples.* UCLA Advanced Research Computing Statistical Methods and Data Analytics. https://stats.oarc.ucla.edu/r/dae/poisson regression/

Vigoureux, T. F., Lee, S., Buxton, O. M., & Almeida, D. M. (2020). Stressor reactivity to insufficient sleep and its association with body mass index in middle-aged workers. *Journal of Sleep Research, 29*(6), e12955.

Work, Family and Health Network. (2018, October 3). *Work, family, and health study (WFHS)*. Inter-university Consortium for Political and Social Research. https://doi.org/10.3886/ICPSR36158.v2

World Health Organization. (n.d.). *Mental health.* https://www.who.int/health-topics/mental-health