Classification of Depression in Childcare Workers

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I. Introduction

ECE Workforce

Early care educators are a critical workforce in our society. Each day, millions of early care educators care for over 10 million children under six who are enrolled in early care and education (ECE).[1] In doing so, they allow millions of parents to leave home in order to play their own part in maintaining the institutions, organizations, and companies that sustain our economy and society. And yet, childcare workers continue to be vastly underpaid and underappreciated. In California, ECE workers' wages consistently fall below the state median wage, and this trend can be seen across all 50 states, as child care workers rank as one of the lowest paid occupations in the nation. In 2022, their average salary was $16,443 - 67% below the national average – and they suffer from poverty wages which are, on average, 7.7 times higher than K-8 teachers.[2] [3] As a result of these incredibly low wages, childcare workers struggle to meet their basic needs, suffering from high rates of economic insecurity as well as food insecurity.[4] [5]

ECE Workforce Mental Wellbeing

Due both in part to the work itself and the conditions surrounding it, childcare work can be extremely difficult. Financial insecurity, lack of job benefits, lack of respect, client satisfaction, and - for many categories of workers such as Black, Latina, and immigrant women - compounded disparate treatment all contribute to the

[1] Otten, Jennifer J. et al. "'The Culture of Health in Early Care and Education: Workers' Wages, Health, and Job Characteristics." *Health Affairs,* vol. 38, no. 5, May 2019, 709-720, 1

[2] Elharake, Jad A. et al. "Prevalence of Chronic Diseases, Depression, and Stress Among US Childcare Professionals During the COVID-19 Pandemic." Preventing Chronic Disease vol. 19, September 2022

[3] McLean, C., Austin, L.J.E., Whitebook, M., & Olson, K.L. (2021). Early Childhood Workforce Index – 2020. Berkeley, CA: Center for the Study of Child Care Employment, University of California, Berkeley.

[4] McLean, C.

[5] "Food Insecurity is Associated with Depression among a Vulnerable Workforce: Early Care and Education Workers." International Journal of Environmental Research and Public Health 18.1 (2021): 170. ProQuest. Web. 2 May 2023.

difficult nature of the work. As a result, ECE workers often display high stress and poor mental health levels. A host of literature on childcare workers' mental wellbeing has emphasized the disproportionately high depression rates among this critical workforce. More than most of the rest of the population, childcare workers' mental health is consistently at risk.

Study Purpose

This study aims to contribute to the literature on ECE workers' wellbeing by applying advanced statistical and machine learning analysis to the 2019 National Survey of Early Care and Education - an existing dataset on the ECE center-based workforce. Rather than just summarizing depression levels amongst childcare workers, this study aims to explore the predictive power of demographics (race, age, etc) in addition to work conditions (wage, union membership) and environment (children in care, perceived respect) as they relate to depression. That is, it aims to determine if these characteristics can accurately predict high levels of depression after being fit to various classification models. In doing so, it will hopefully identify some of the primary possible causes for depression in childcare workers, and situate these causes within the broader landscape of ECE research and policy.

II. Related Work

Overview of Depression Rates among Childcare Workers

The vast majority of existing literature on childcare workers' depression rates has suggested that childcare workers have depression rates far higher than those of the rest of the adult population. Studies that survey childcare workers have found sample depression rates between 9-40% of the sampled population. [6] [7] [8] [9] [10] [11] These rates have worsened with the 2019 COVID-19 pandemic; in one 2022 study 45.7% of surveyed workers screened positive for depression.[12] With the exception of Hamre's & Pianta's study, all of these studies reported depression rates higher than the average depression rates at the time of the studies, considering both the whole adult population and the relevant population of similar demographics. Both Hamre & Pianta and Elharake et al. found that depression scores in home-based workers were lower on average compared to center-based workers.

Overview of Previous Research

Previous Studies' Goals

The last ten years has seen an increase in literature addressing the mental wellbeing of childcare workers, though there remains a limited reserve of research. In the past, much of existing literature has focused on childcare worker wellbeing as a means of improving childhood development outcomes. That is, many authors have argued that worker wellbeing is crucial, particularly as a means for maintaining a positive caretaking environment for young children.[13] [14] [15] Hamre & Piante analyzed the effect that a childcare worker's

[6] Hamre, Bridget K, and Robert C Pianta. "Self-Reported Depression in Nonfamilial Caregivers: Prevalence and Associations with Caregiver Behavior in Child-Care Settings." Early childhood research quarterly 19.2 (2004): 297–318.

[7] Whitaker, Robert C et al. "The physical and mental health of Head Start staff: the Pennsylvania Head Start staff wellness survey, 2012." Preventing chronic disease vol. 10 E181. 31 Oct. 2013,

[8] Whitaker, Robert C. Tracy Dearth-Wesley, Rachel A. Gooze, Workplace stress and the quality of teacher–children relationships in Head Start, Early Childhood Research Quarterly,Volume 30, Part A, 2015,Pages 57-69,

[9] Linnan, Laura, et al. "The Health and Working Conditions of Women Employed in Child Care." International Journal of Environmental Research and Public Health, vol. 14, no. 3, Mar. 2017, p. 283.

[10] Otten, Jennifer L.

[11] Asae, Oura et al. "Factors Related to Depression Among Childcare worker;Cross-Sectional Study in Hokkaido, Japan." 札幌医学雑誌 = The Sapporo Medical Journal 86.1-6 (2017): 25–32. Print.

[12] Elharake, Jad. et al.

[13] Hamre, Bridget K., and Robert C. Pianta,

[14] Deery–Schmitt, D. M., & Todd, C. M. (1995). A conceptual model for studying turnover among family child care providers. Early Childhood Research Quarterly, 10, 121–143, 122.

[15] Elharake, Jad et al.

depression might have on the positive development and education of children, finding an association between self-reported depressive symptoms in childcare workers and the quality of their interactions with children. Their findings argued that depressed caretakers were more likely to be sensitive and withdrawn, engaging in negative interactions with children.

While this impact is certainly important, it is also important to study child care worker wellbeing for the sake of the workers themselves, rather than for the sake of the children they serve. Analyzing literature about childcare providers pre-2013, Paula Gerstenblatt et al. identified this need for research on the wellbeing of workers outside of the lens of the quality of the care that they provide.[16]

Key Factors Contributing to Depression Rates of Childcare Workers

Curbow et. al described the concept of "stressors" in the context of past job stress literature as the "work-related environmental conditions or exposures that can potentially affect the psychological, social, and physiological health of an individual." [17] These include both the objective conditions of the work environment, in addition to workers' individual perceptions of it.[18] Throughout the past few decades, child care researchers have attempted to define several key categories of stressors for childcare workers, specifically as they relate to their mental health. Otten et al. identified some of these categories: compensation (including pay, benefits, and leave), classroom structure (including number of students and teacher-to-child ratios), and center environment (including aspects of workplace culture).[19] These categories and others will be discussed in further detail. Note that the following sections may mention working conditions or external factors that contribute to "stress" or "job dissatisfaction." While these phenomena are distinct from clinical depression, this study assumes that negative experiences, stress, and general unhappiness may contribute to depressive symptoms.

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[16] Gerstenblatt, Paula et al. "Not Babysitting: Work Stress and Well-Being for Family Child Care Providers." Early childhood education journal 42.1 (2014): 67–75, 68.

[17] Curbow, Barbara et al. "Development of the Child Care Worker Job Stress Inventory." Early childhood research quarterly 15.4 (2000): 515–536, 515.

[18] Curbow, Barbara et al, 516.

[19] Otten, Jennifer L, 710.

Compensation

As mentioned, childcare workers are amongst the lowest paid professionals in the workforce and much existing literature on workers' stress and mental health has suggested that "inadequate income is one of the most stressful factors identified by family child care providers." [20] In fact, there is a clear link between the "material deprivation and stress associated with low income" and individuals' physical and mental health." [21] In their 2017 study, Linnan et. al. demonstrated this apparent link, determining that lower-income childcare workers were more likely to report higher levels of depressive symptoms.

Not only are childcare workers unfairly compensated, they often lack key job benefits such as sick leave, healthcare, and retirement. Studies have found 25-30% of ECE to lack any form of health insurance and, according to recent research on California's Early Care and Education sector, only 39-50% of childcare workers in centers (depending on job title) lack any retirement savings. [22] [23] This lack of benefits subjects workers to long term health, safety, and financial risks, contributing to stress and poor mental wellbeing. This study thus hypothesizes that low wages and overall income, as well as a lack in key benefits such as healthcare will be negatively correlated with psychological wellbeing as measured by depressive symptoms.

Center Conditions and Environment

It is well-documented that childcare work can be highly draining, and comes with many emotional and physical demands.[24] [25] Children's behavior, as well as client and colleague relations are all components of the ECE workplace environment that contribute to childcare workers' stress and wellbeing on a daily basis. Through focus groups, Gerstenblatt et al. identified several aspects of childcare work which are highly

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[20] Gerstenblatt, Paula et al., 68.
[21] Otten, Jennifer L. et al., 710.
[22] Otten, Jennifer L. et al., 710.
[23] Powell, Anna. "California's early educators can't afford to retire," Center for the Study of Childcare Employment.

[24] Gerstenblatt, Paula et al., 72.
[25] Otten, Jennifer L. et al., 710.

emotionally draining including a persistent lack of respect, striving for parent satisfaction, and the multiple jobs that they must perform simultaneously (i.e. second parent, child development expert, advisor for parents, etc.).[26] Indeed, Jeon et al. found that children's challenging behaviors was positively associated with emotional exhaustion and that "child care chaos" (perceived chaos within the work environment) was the strongest predictor of caretaker's depressive symptoms, stress, and emotional exhaustion.[27] The ability to take a break from stressful work conditions may also play a role in workers' wellbeing; a Japanese study on nursery workers found that the ability to take paid holidays was associated with lower levels of depression.[28] This present study thus hypothesizes that chaotic work environments (measured by the number, age, and behavior of children) have a negative impact on worker wellbeing, in addition to measures of inflexibility in the workplace (measured by variables such as hours/months worked).

Lack of Support and Recognition

Childcare workers are underappreciated and undervalued for their critical professional work. Through focus groups, Otten et al. identified "societal and parental disrespect" as a key job stressor for workers, and this sentiment is in line with the general consensus in ECE research.[29] These focus groups "depicted a workforce whose members felt undervalued by society."[30] Indeed, childcare workers often report that they're seen as "babysitters" rather than experts or professionals, and this contributes to their daily stress about their job.[31]

Due to the conditions of their work environment, many childcare workers lack critical support from their centers. Otten et al. found that, even when center directors wanted to support workers' mental and physical health, they often lacked the resources to provide it .[32] Asae et al. found that the ability to consult a

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[26] Gerstenblatt, Paul et al., 70.
[27] Jeon, Lieny, Cynthia K. Buettner, and Ashley A. Grant. "Early Childhood Teachers' Psychological Well-Being: Exploring Potential Predictors of Depression, Stress, and Emotional Exhaustion." Early education and development 29.1 (2018): 53–69., 62.
[28] Asae, Oura et al. "Factors Related to Depression Among Childcare worker;Cross-Sectional Study in Hokkaido, Japan." 札幌医学雑誌 = The Sapporo Medical Journal 86.1-6 (2017): 25–32, 28.
[29] Otten, Jennifer L. et al., 712
[30] Otten, Jennifer L., 714.
[31] Gerstenblatt, Paula et al., 71.
[32] Otten, Jennifer L., 712.

supervisor for advice, as well as a lack of job assessment were both associated with higher risks of depression.[33] Where more support is accessible, some studies have shown a positive correlation between job training and worker mental wellbeing; Todd & Deery-Schmitt (1996) found that training was associated with lower levels of job stress in higher educated workers.[34] Otten et al. and Jeon et al. similarly found that access to professional training opportunities and higher levels of job competency were associated with improved mental wellbeing [35] [36]

This study thus hypothesizes that perceived respect, support, and professional development opportunities have positive effects on workers' mental wellbeing.

The previous literature on job stressors in childcare work can be summarized by the following table, and motivates further analysis of several variables as outlined in Section IV: Variable Selection.

Table 1: Job stressors based on literature.

Job Stressor	Previous Studies
Financial Stress: *childcare workers are severely underpaid and lack crucial benefits.*	Gerstenblatt et al., Otten et al, Linnan et al.,
Working Conditions and Environment: *childcare workers work under highly stressful and emotionally draining conditions.*	Gerstenblatt et al., Otten et al, Jeon et al., Asae et al.
Lack of Support and Recognition: *childcare workers are not adequately recognized or supported for the critical work they do.*	Gerstenblatt et al, Otten et al, Todd & Deery Schmitt, Jeon et al., Asae et al.

[33] Asae, Oura et al., 28.
[34] Todd, Christine M., and Deanna M. Deery-Schmitt. "Factors Affecting Turnover Among Family Child Care Providers: A Longitudinal Study." Early childhood research quarterly 11.3 (1996): 351–376, 368.
[35] Otten, Jennifer L. et al., 711.
[36] Jeon, Lieny et al., 60.

III. Methodology

`This study is primarily a classification task defined as: predicting depression based on variables related to compensation/financial stress, working conditions and environment, lack of support and recognition, as well as demographic information.

Center for Epidemiological Studies-Depression (CES-D)

A 2016 Updated Literature Review of the field of Early Childhood Educators identified an issue in the existing literature; a lack of consistency in terms of methodological frameworks for studying childcare worker wellbeing. Indeed, existing literature has explored varying methodological approaches for studying childcare worker wellbeing. Many studies have conducted focus groups to better understand the general wellbeing of workers (Otten et al., Gerstenblatt et al.), while others have focused on outcomes of worker burnout, turnover, and job satisfaction (Manlove, Deery-Schmitt & Todd, McClelland). However, there has been some recent accord in the use of established psychological questionnaires as a quantitative measure for mental well-being. In particular, a small handful of studies, especially in the past 10 years, have utilized the Center for Epidemiological Studies-Depression questionnaire (Hamre & Pianta, Whitaker et al., Linnan et al., Otten et al., Elharake et. al., Asae et al.). Originally published in 1977 the CES-D is a 20-item questionnaire that measures depressive symptoms such as restless sleep, poor appetite, and loneliness.[37] Scored out of 60, the CES-D can be measured as both a total self-reported depression score, or as a yes/no indication of surpassing a cutoff value of 16 (indicating a high risk of depressive disorder). In 2012, a study of Head Start staff utilized the CES-D score as a quantitative measure for depression and since then, others (Linnan et al., Otten et al., Elharake et al., Asae et al.) have also used the CES-D in their research.

[37]"Center for Epidemiological Studies-Depression," American Psychological Association, 2011.

Framework

In keeping with this more recent methodology, this study measures childcare worker depression using responses to the CES-D questionnaire as reported by the 2019 National Survey of Early Care and Education. The survey, which observes 5192 workers across 179 different features, measures depression with respect to both the raw score *WF9_CESD7_TOT* and the indicator variable *WF9_CESD7_CUT* which represents whether or not a given respondent is suspected of major depressive disorder based on a select number of questions from the CESD-7. Due to a high imbalance in the data the latter, *WF9_CESD7_CUT,* was chosen to be the target variable for classification.

From the 179 different features, 28 individual variables were utilized as independent variables, chosen primarily based on an array of existing literature which suggested their impact on worker stress and depression. The process of variable selection is described in detail in Section IV: Variable Selection.

For modeling purposes, 14 categorical variables were split into separate dummy-encoded variables, and nine ordinal variables were supplemented with indicator columns representing a response of "I don't know/Refuse" (process described in Section IV: Data). This pre-processing resulted in a working dataset with 71 separate independent variables. Finally, the dataset was split into three datasets - 80% of the data for model training and 10% each for model development and testing.

Finally, three separate classification methods were trained on the training dataset with various approaches to adapting to the imbalance within the dataset.

Techniques

Existing literature is fairly limited in the statistical methods applied to studying childcare worker wellbeing. Most quantitative analyses have outlined descriptive statistics within a population of study (Otten et al., Linnan et al.). These studies calculate depression rates within a given sample and along various lines such as income, center vs home-based, education level, etc.. They study t-scores, confidence intervals, and standard errors to better situate the findings within statistical analysis. Recently, some other authors have performed multivariate regression methods in order to begin understanding the association between particular working conditions and childcare worker wellbeing. Asae et al., Jeon et al., and Elharake et al (2016, 2018 and 2022, respectively), all conducted multi-linear or logistic regression analysis using the CES-D as a quantitative measure for depression.

This study provides a combination of and expansion upon those techniques already used in existing research. Initially, a logistic regression model was trained on the data and variable coefficients, p-values, and confidence intervals of the resulting regression were analyzed. In order to expand upon previous research, additional decision tree (CART) and Random Forest classification models were trained to predict the dependent variable, *WF9_CESD7_CUT*. These two particular models were intended to provide additional insight into childcare worker wellbeing through analysis of variable importance scores, decision tree visualization, and hyperparameter training for variable selection. Finally, analysis of threshold tuning and class weights was applied to each model throughout the study in order to account for the high level of imbalance in the dataset.

IV. Data

Data Origins

The survey used for this study was funded by the Office of Planning Research, and Evaluation within the Administration for Children and Families (ACF), U.S. Department of Health and Human Services, and the research itself was conducted by NORC, at the University of Chicago. Using state-based and national agencies' provider lists, researchers compiled a sampling frame of listed providers. They used a multistage probability design and clustering techniques for their survey design. In addition, due to the importance of policy regarding low-income workers, low-income areas were oversampled in the sampling frame. The final NSECE consists of four separate surveys which address different sectors of the CCEE Workforce - households with children under 13, home-based providers, center-based providers, and center-based workforce. This study particularly focuses on the center-based workforce, which is the only group that contains information of workers' self-reported health scores, including depression.

Dataset Contents

The 2019 NSECE data observes 5192 workers across 179 different features which are detailed in the NSECE User Guide. These features can be divided into several main categories: Qualifications and Experience, Employment Schedule and Compensation, Activities in the Classroom, People in the Classroom, Staff Attitudes and Orientation to Caregiving, and Demographics. From the 179 features, this study selects 28 relevant ones (detailed in Section IV: Data) as independent variables.

With the exception of a few continuous variables, most of the variables in the dataset are either categorical or ordinal variables. Throughout the dataset, values of -1 refer to a respondent answer of "Don't Know/Refused/No Answer." Values of -8 refer to data "spawned from [a] center with only administrative data." 483 rows where the target variable was equal to -8 were removed from the data in the pre-processing phase.

The survey also contains data on worker wellbeing including self-reported physical health, stress level, and mental health scores. To assess mental wellbeing, the survey poses seven questions from the Center for Epidemiological Studies-Depression (CES-D). Each question asks the individual the frequency of a given depressive symptom over the course of the last week. The NSECE contains seven out of the 20 original CES-D questions: poor appetite, trouble concentrating, restless sleep, felt sad, felt depressed, felt everything was an effort, and could not get going. Two more features in the dataset summarize the results of this information: *WF9_CESD7_TOTAL* measures the total score across all seven questions, and *WF9-CESD7_CUT* - the relevant target variable for this study - is a boolean value indicating whether or not the individual's total score is above a cut off of 8. A total score of 8 or higher categorizes the respondent as being suspected of major depressive disorder.

Variable Selection

The classification task defined by this study considers the target variable to be *WF9_CESD7_CUT*, indicating whether or not a respondent is suspected of major depressive disorder.

Out of the 179 variables in the dataset, this study utilizes 29 as independent variables. As a first step, variables were chosen due to their hypothesized relevance to the research question. That is, variables were chosen if previous literature suggested them to be areas of interest or if they were individually deemed to be areas of interest by the author of this study. *Table 1* and *Table 2* can be combined to summarize the use of previous literature to guide variable selection; after having categorized job stressors into three main categories as indicated by the literature, we can identify variables in the dataset that fit these categories of interest. These relevant variables were included in addition to demographic variables such as race, educational status, and household income, etc.. Finally, in order to ensure significant predictors had not been overlooked, a preliminary logistic regression model was trained on the entire dataset. All variables with p-value less than 0.1 were added to the list of variables. A final list of variables used for classification and their descriptions is shown in *Figure 1*.

Table 2: Variables of interest.

Job Stressor	Variables of Interest
Financial Stress and Compensation	Household income, Wage, Government assistance, Health insurance
Work Conditions and Environment	Work Months, Center funding, Union status, Number of children, Behavior of children
Support and Recognition	Perceived respect, Parent-worker relationship, Professional development opportunity, Availability of help

***Table 3*: Independent variables.**

Variable Name	Variable Description
Categorical	
WF9_CHAR_GENDER	Gender
WF9_CHAR_RACE	Race
WF9_CHAR_HISP	Hispanic
WF9_CAREER_UNION	Union membership
WF9_CHAR_COUNTRY_BORN	Country of birth
WF9_CHAR_MARITAL	Marital status
WF9_CHAR_HEALTH_INSRNCE	Health insurance
WF9_CHAR_GOVT_PRGM	Respondent gets government financial aid
CB9_SERVE_0TO3YRS	Center-based provider serves children 0 to 3 years
WF9_WORK_PLAN	Respondent plans daily activities of children in class
WF9_C5_OVER4HR_TRAIN	Respondent received >=4 hours of training on how to use curriculum
WF9_PROFDEV_WRKSHP	Professional development in past 12 months: participated in workshops
WF9_WORK_REVIEW	Respondent receives formal review and feedback once a year
CB9_RVNU_CENTER_FUND_COMBO	Combination of government revenue sources center receives funding from
Ordinal	
WF9_CHAR_EDUC	Educational attainment
WF9_CHAR_HHINCOME	Household income
WF9_WORK_YRS	Number of years in program
WF9_CAREER_EXPERIENCE	Years caring for children under 13
WF9_WORK_HRS_CAT	Hours worked per week
WF9_A19_HRS_SKILLS	Hours per month on prof dev activities
WF9_WORK_RESPECT	Agreement with: my co-workers and I are treated with respect on a daily basis
WF9_WORK_HELP_AVAILABLE	Agreement with: I have help dealing with difficult children/parents
WF9_WORK_BEHAVIOR	Frequency: There were children with behavioral problems that were hard to deal with
WF9_WORK_PRNTS_TALK	Frequency: How often last week respondent spoke with parents about child's family life
Ratio	
WF9_WORK_MONTHS	Number of months out of last 12 months respondent has worked
WF9_CL6A_B_PRCNT_CHCLASS_BLACK	Percent of children in class that are Black
WF9_ATTITUDES_PMS_PROG	Parental Modernity Scales-Progressive Belief Subscale

This study uses the NSECE center-based workforce data in isolation; since the dataset contains no identifying information, no other data was merged as part of the study.

Exploratory Analysis

8.349% of respondents have a total depression score that surpasses 8 points, pointing to major depressive disorder. Out of the previous literature, these levels are closest to Hamre & Pianta 2004 findings, which reported depression among 9.4% of a sample of 1217 caregivers. However, they are low compared to the current overall adult women population (10.5%), and especially low compared to most other previous studies of childcare workers, which showed rates up to 40% .[38] These levels may in part be due to the fact that the NSECE only poses seven out of the 20 total CESD-7 questions. It is possible that in truncating the survey part of the larger picture of respondents' mental wellbeing was lost. This low percentage of depressed respondents revealed a high level of imbalance within the data, which was necessary to keep in mind when developing predictive models.

During EDA, many other demographics of the survey population were analyzed including gender, race, country of birth, and household income. The population was majority white, non-hispanic, female, and US-born. While the majority of respondents had some form of employer-provided health insurance (28.9%) or directly purchased their own health insurance (17.2%), the next largest group (15.5%) had no health insurance at all. 22.7% of respondents reported a household income of over $60000, while 43.7% of respondents came from households earning $30,000 or less each year. Among the latter group, 16.4% reported household incomes of under $15000 annually, placing them in at least the bottom 2nd percentile for all occupations nationwide. Analyzing the seven different household income brackets, these respondents with the lowest reported annual household income had the highest rates of depression. Other than respondents who refused to answer, those in the highest income bracket (>$60000) had the lowest depression rates. Finally, only 14.7% of respondents reported receiving financial aid or in-kind assistance from the government.

[38] "Major Depression," National Institute of Mental Health, Jan. 2022.

Tables 4 and 5: Distribution of demographic variables.

Demographic Variables

		n	%
Gender			
	Male	112	0.02
	Female	4534	0.87
	Refuse/IDK	63	0.01
Race			
	White Only	2825	0.54
	Black or African American Only	991	0.19
	Asian Only	210	0.04
	Other	215	0.04
	Refuse/IDK	468	0.09
Hispanic			
	Yes	1119	0.22
	No	3462	0.67
	Refuse/IDK	128	0.02
Country of Birth			
	U.S., including territories	3822	0.74
	Mexico	194	0.04
	Other	571	0.11
	Refuse/IDK	122	0.02
Marital Status			
	Never married, not living with partner	1472	0.28
	Married or living with partner	2454	0.47
	Separated or Widowed	240	0.05
	Divorced	369	0.07
	Refuse/IDK	174	0.03
Educational Level			
	Less than high school	85	0.016
	GED or high school equivalency	126	0.02
	High school graduate	769	0.15
	Some college but no degree	1279	0.25
	Associate degree	834	0.16
	Bachelor's degree	1168	0.22
	Graduate or professional	424	0.08
	Refuse/IDK	24	0.004
Household Income			
	Less than $15000	719	0.14
	$15001 to $30000	1209	0.23
	$30001 to $45000	611	0.12
	$45001 to $60000	501	0.09
	$60001 or more	1006	.19
	Refuse	663	.13
Government Financial Aid			
	Yes	647	0.12
	No	3886	0.75
	Refuse/IDK	176	0.03

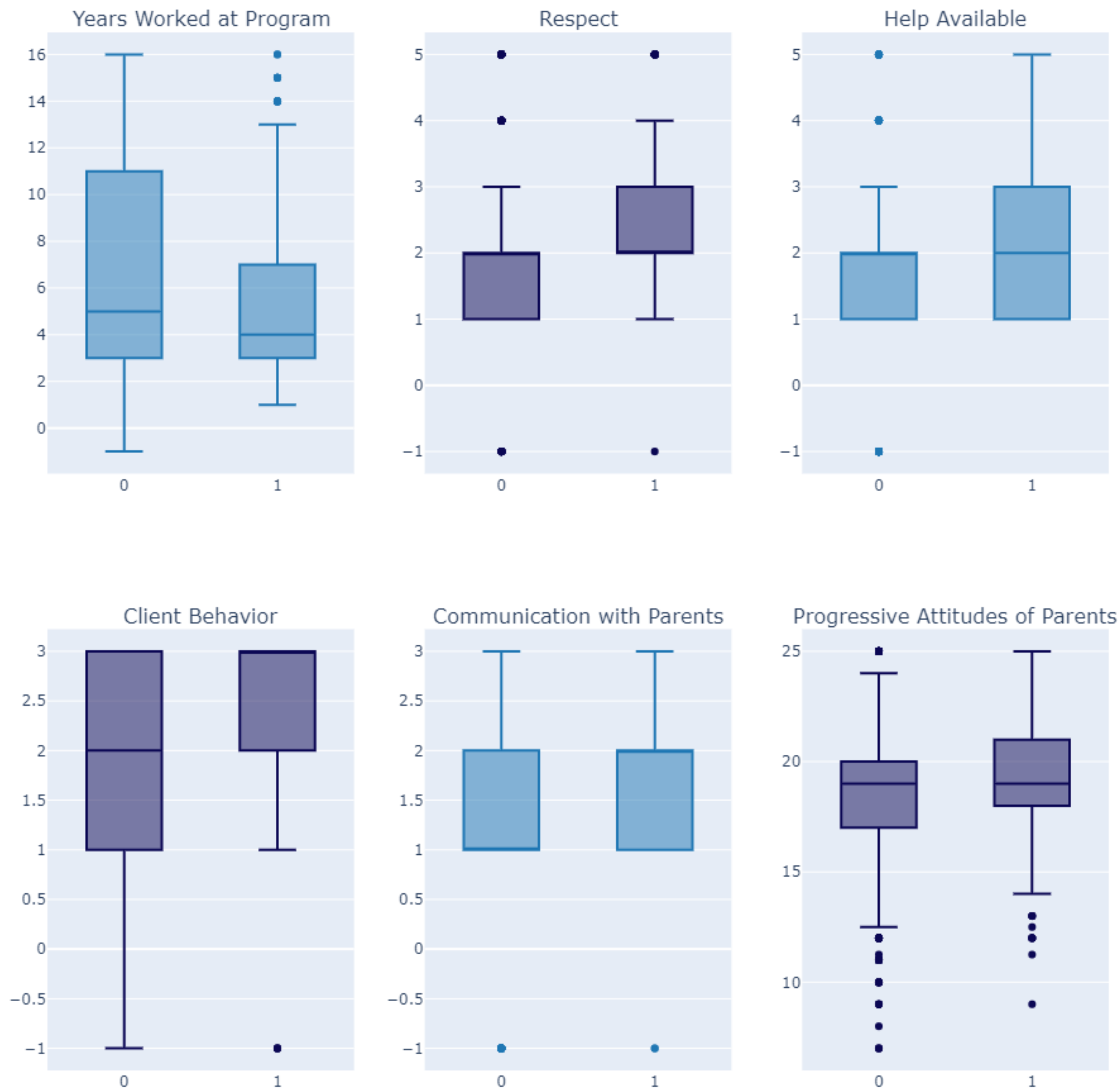
Health Insurance and Union Membership

		n	%
Health Insurance			
	No Coverage	716	0.14
	Private from R's workplace, only	1274	0.25
	Private from workplace, other type(s)	67	0.013
	Private through spouse or partner	285	0.06
	Private purchased directly	816	0.16
	Private through state, local govt or community program	304	0.06
	Medicaid, Medicare, or Military	644	0.12
	Other or Combination	581	0.11
Union Membership			
	Yes	457	0.09
	No	4192	0.81

All remaining percentages come from data points that were spawned from administrative data rather than individual survey responses.

Figure 1: Depression Rates: Demographic Variables

Figure 2: Depression Rates: Work Environment Variables



Data Pre-Processing

Separate data processing steps were performed on ordinal and categorical variables in order to address the unique structure of the data. For ordinal variables (see *Table 3*), the value of -1 indicating a response of "I Don't Know/Refuse" was incompatible with the ordered nature of the remaining values. In order to address this inconsistency, an additional variable titled *varname_R* was created for each ordinal variable *varname* indicating whether the original response was "I don't know/Refuse" for *varname*. This extra feature served as an adjustment factor within the models for each corresponding original variable.

Next, each categorical variable (see *Table 3*) with *k* possible values was split into *k-1* dummy variables using Pandas get_dummies function. In order to improve the interpretability of the logistic regression model, all numerical values of -1 (indicating "I don't Know/Refuse) were replaced with 999. Then, the functionality of get_dummies is such that the first substantial category of each variable was automatically dropped to avoid model collinearity. Thus, all categorical dummy variables are indicated as follows given the original variable *varname* and possible values [*a, b, c ..., 999*]*: varname_b, var_c,* and so on until finally *varname*_999, corresponding to responses of "I don't Know/Refuse."

V. Experiments

Using the NSECE center-based workforce data, this study trained three separate models to identify factors predictive of depression. All models were trained on the same set of observations across all selected features. Training data was labeled by the dependent variable *WF9_CDSD7_CUT*, or whether or not a given respondent's total self-reported depression score suggested major depressive disorder. Three different machine-learning techniques were applied: logistic regression, CART classification, and RandomForest.

Before modeling, data was randomly split into three groups - 80% for training, 10% for model development, and 10% for final testing. The three models are described individually in the following sections.

Metrics

The NSECE data is heavily biased with respect to the target variable, $WF9\_CESD\_CUT$. That is, out of 4168 respondents, only 348 or 8.34% of respondents had a total depression score suggesting major depressive disorder. Given this imbalance, judging model performance by accuracy can be misleading, and other metrics must be considered. In particular, F1 score - the harmonic mean of precision and recall - and precision will be considered as primary measures of performance. These metrics are generally considered better suited to handle unbalanced data, since they take into account the performance of both classes, rather than just the overall model. Additionally, the sensitivity or true positive rate (TPR) of predictions will be compared to the recall or false negative rate (FPR) in order to maintain a balance between correctly identified positive and negative predictions. Accuracy will be used as a final measure to assess the performance of differing models. By combining these measures, the study attempts to gain a better understanding of each model's predictions past just accuracy.

Models

Baseline Model

To create a baseline of comparison, an initial baseline model was considered. This initial model predicted only the majority class where $WF9\_CESD7\_CUT = 0$, indicating no suspected depression. Under this baseline model, the TPR and FPR are 0, while the model accuracy is 93%. Model F1 and precision could not be calculated since the model made no positive predictions. These percentages indicate a slightly lower frequency of depression within the development data as compared to the full sample (which has a depression rate of 8.349%).

Logistic Regression

For the first model, python package *sklearn* was used to train a logistic regression model on the labeled training data, and as a form of regression diagnostics, Variable Inflation Factor (VIF) scores were analyzed. Using the initial training data, several variables showed high VIF scores including $WF9\_CHAR\_YEAR\_BORN$ which had a VIF score of over 100. When this feature was removed from the training data, all other feature VIF scores remained below five.

Retraining and applying this updated model to the test set using a prediction threshold of 0.5, the F1 score was 0.117. TPR was 0.066, only slightly higher than that of the baseline model, while the FPR was 0.005. Model precision was 0.5, while the model accuracy was 92.8%. Additionally the model's $Pseudo\ R^2$ was 0.1831.

These results reflected the high imbalance within the data; the model made very few positive predictions, identifying only two out of 30 true positive cases. In order to account for this imbalance, ROC curve analysis was performed to determine the efficacy of various thresholds. The AUC for the given ROC Curve on the testing data was 73.16%, and the specific threshold which would maximize both the TPR and FPR was found to be 0.064. Adjusting the probability threshold for positive predictions to be 0.064 improved the TPR significantly, but at the great cost of the FPR and precision. Using the determined optimal threshold of 0.064, the model made a total of 18 correct positive predictions, but incorrectly identified 90 negative observations as positive. Various other intermediate thresholds were also analyzed, and their outcomes are shown in the table below.

Figure 3: ROC Curve

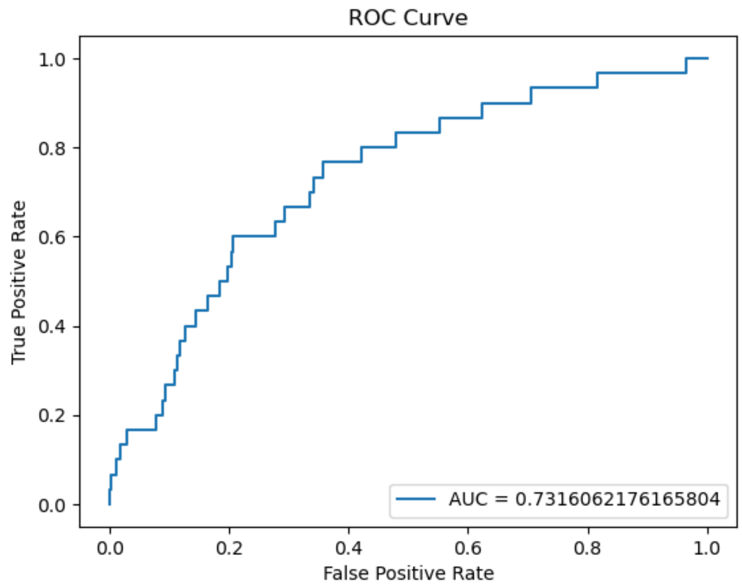


Table 6: Prediction thresholds for logistic regression.

	Baseline	T = 0.5	T = 0.2	T = 0.1	T = 0.08	T = 0.064
F1	n/a	0.117647	0.171429	0.260870	0.236025	0.231579
TPR	0	0.066667	0.200000	0.600000	0.633333	0.733333
FPR	0	0.005181	0.200000	0.233161	0.290155	0.357513
Precision	n/a	0.500000	0.150000	0.166667	0.145038	0.137500
Accuracy	0.93	0.927885	0.860577	0.754808	0.704327	0.649038

Finally, P-value analysis of the logistic regression model was performed. Variables were determined to be statistically significant based on a 5% level of significance, or $\alpha = 0.05$.

CART Classification

Custom Loss Function

The second model implemented a CART classification model - a predictive algorithm represented by a binary decision tree. The model was trained using sklearn's DecisionTreeClassifier, and GridSearchCV to determine the complexity parameter (*ccp_alpha*) based on a custom loss function. This loss function was implemented using "make_scorer" from scikit-learn, which wraps custom performance metrics or loss functions for use in GridSearchCV. In order to adjust for the unbalanced data, the custom loss function multiplies the weight on false negatives by a chosen weight.

$$Loss = fp + fn * w$$

This loss function (shown above) was used for cross validation training of hyperparameter *ccp_alpha.* Here, w refers to a manually chosen weight applied to false negative classifications. In order to visualize the performance of the model across varying weights, a TPR vs. FPR graph was created. Each point on the curve represents the TPR and FPR of the best fit classification tree under a given weight w where $w \in \{1, 25, 50... 500\}$. Finally, the model with the highest performance as measured by F1 score was analyzed for variable importance measures and tree visualization.

Class Weights

In addition to the custom loss function used during cross validation, one more analysis of class weighting was performed using the F1 scoring metric during cross validation. For this analysis, cross validation was performed to find the optimal model given each potential weighting in a set of class weights. Weighting was determined to start at {Class 0: 0.3, Class 1: 0.7}, and at each step Class

1 increased by 0.01 (weights should sum to 1, thus Class 0 decreases by the same amount). In other words, $\{0: i - 1,\ 1: i\}\ where\ i \in \{0.7, 0.71, 0.72,\ \ldots\ ,\ 1\}$. This process is shown in *Figure 4.* The resulting TPR and FPR for various class weights was visualized similarly to above.

Figure 4: Model optimization for differing class weights.

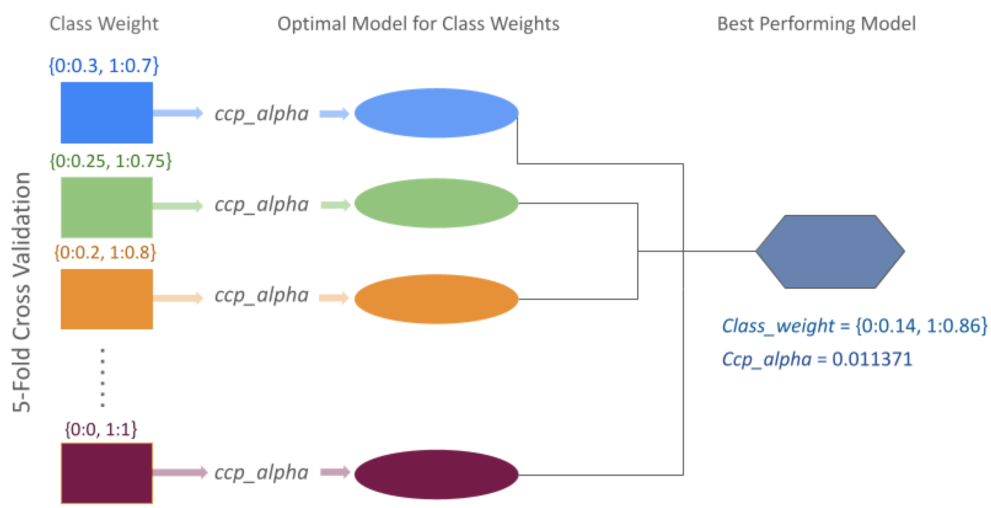
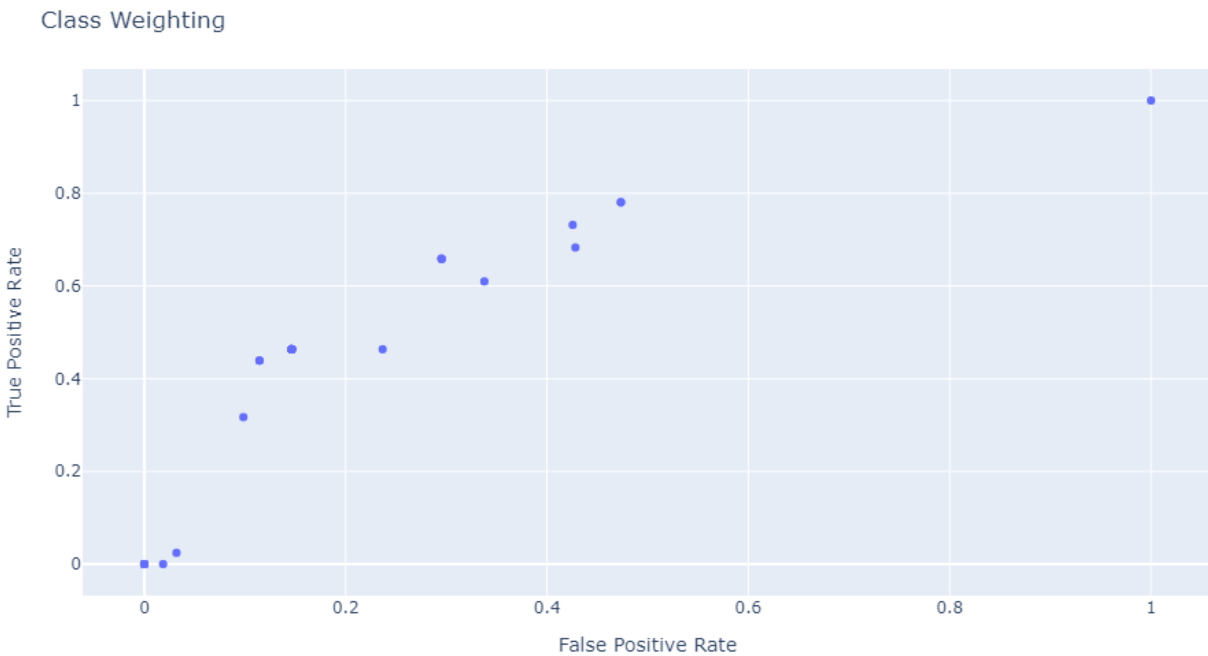


Figure 5: TPR vs FPR for adjusted class weights. Each point represents the TPR and FPR of the cross-validated optimal model for a given class weighting, using F1 scoring.



Finally, the model with the highest performance on the development data (as measured by F1 score) was applied to the testing data and then analyzed for variable importance scores and tree visualization.

Random Forest

Following the same methods as for the CART classification, this study used sklearn to train a random forest classifier - a machine learning model which aggregates the predictions of a number of separate decision trees. This study implemented GridSearchcv with 5-fold cross validation in order to find the optimal hyperparameter of max_features, using the same custom loss function as before.

$$Loss = fp + fn * w$$

Unfortunately, due to the highly time-intensive process, repeated cross-validation of hyperparameters was not possible as it was for the single decision tree model. However, one more instance of cross validation was performed to find the optimal hyperparameter max_features - cross validation in this case optimized F1 score, and assumed the optimal class weighting as determined to be optimal for the single decision tree ({0:0.14, 1:0.86}).

VI. Results

Logistic Regression

The full results of the logistic regression model are shown below. P-value analysis of the logistic regression model determined 11 variables to be statistically significant from zero: *WF9_WORK_YRS, WF9_WORK_BEHAVIOR, WF9_WORK_HELP_AVAILABLE, WF9_WORK_RESPECT, WF9_WORK_PRNTS_TALK, WF9_ATTITUDES_PMS_PROG, WF9_CAREER_EXPERIENCE_R, WF9_WORK_BEHAVIOR_R, WF9_PROFDEV_WRKSHP_999, CB9_RVNU_CENTER_FUND_COMBO_4,* and *CB9_RVNU_CENTER_FUND_COMBO_7.* In particular, out of these 11, six variables were statistically significant at the 0.01% level. This section of the study will provide further detail on these six variables.

Table 7: Logistic regression summary.

Dep. Variable:	WF9_CESD7_CUT	**No. Observations:**	3331
Model:	Logit	**Df Residuals:**	3259
Method:	MLE	**Df Model:**	71
Date:	Fri, 21 Apr 2023	**Pseudo R-squ.:**	0.1831
Time:	20:38:41	**Log-Likelihood:**	-779.36
converged:	False	**LL-Null:**	-954.05
Covariance Type:	nonrobust	**LLR p-value:**	2.209e-38

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
const	-7.2943	1.030	-7.082	0.000	-9.313	-5.276
WF9_WORK_YRS	-0.0703	0.022	-3.269	0.001	-0.112	-0.028
WF9_CAREER_EXPERIENCE	0.0055	0.054	0.102	0.919	-0.101	0.112
WF9_CHAR_EDUC	-0.0653	0.056	-1.160	0.246	-0.176	0.045
WF9_A19_HRS_SKILLS	-0.0471	0.056	-0.845	0.398	-0.156	0.062
WF9_WORK_HRS_CAT	0.0396	0.050	0.792	0.428	-0.058	0.138
WF9_WORK_MONTHS	0.0169	0.025	0.665	0.506	-0.033	0.067
WF9_WORK_BEHAVIOR	0.5724	0.105	5.461	0.000	0.367	0.778
WF9_WORK_HELP_AVAILABLE	0.2001	0.072	2.774	0.006	0.059	0.342
WF9_WORK_RESPECT	0.4466	0.072	6.178	0.000	0.305	0.588
WF9_CHAR_HHINCOME	-0.0757	0.062	-1.218	0.223	-0.198	0.046
WF9_WORK_PRNTS_TALK	0.3518	0.101	3.489	0.000	0.154	0.550
WF9_ATTITUDES_PMS_PROG	0.1141	0.029	4.000	0.000	0.058	0.170
WF9_CL6A_B_PRCNT_CHCLASS_BLACK	-0.0053	0.003	-1.817	0.069	-0.011	0.000
WF9_WORK_BGCHK_EASY	0.1140	0.083	1.366	0.172	-0.050	0.278
WF9_WORK_YRS_999	-16.7791	6306.559	-0.003	0.998	-1.24e+04	1.23e+04
WF9_CAREER_EXPERIENCE_999	1.5749	0.681	2.312	0.021	0.240	2.910
WF9_CHAR_EDUC_999	-14.6527	1467.945	-0.010	0.992	-2891.773	2862.467
WF9_A19_HRS_SKILLS_999	-0.4274	0.851	-0.502	0.616	-2.096	1.241
WF9_WORK_HRS_CAT_999	1.8715	1.173	1.596	0.110	-0.427	4.170
WF9_WORK_MONTHS_999	-0.3147	0.855	-0.368	0.713	-1.990	1.360
WF9_WORK_BEHAVIOR_999	1.9307	0.793	2.434	0.015	0.376	3.486
WF9_WORK_HELP_AVAILABLE_999	-13.5564	1085.433	-0.012	0.990	-2140.966	2113.853
WF9_WORK_RESPECT_999	-22.8995	2.95e+05	-7.76e-05	1.000	-5.79e+05	5.79e+05
WF9_CHAR_HHINCOME_999	-0.4110	0.374	-1.099	0.272	-1.144	0.322
WF9_CL6A_B_PRCNT_CHCLASS_BLACK_999	-0.2502	0.198	-1.266	0.205	-0.638	0.137
WF9_WORK_BGCHK_EASY_999	0.1936	0.540	0.359	0.720	-0.865	1.252
WF9_CHAR_RACE_2	0.1187	0.207	0.573	0.567	-0.287	0.524
WF9_CHAR_RACE_3	0.1645	0.396	0.415	0.678	-0.611	0.940
WF9_CHAR_RACE_8	0.0925	0.284	0.326	0.744	-0.463	0.648
WF9_CHAR_RACE_999	-0.1096	0.369	-0.297	0.766	-0.832	0.613
WF9_CAREER_UNION_2	-0.2913	0.252	-1.154	0.248	-0.786	0.203
WF9_CAREER_UNION_999	0.3017	0.920	0.328	0.743	-1.501	2.105
WF9_CHAR_HISP_2	0.3496	0.218	1.603	0.109	-0.078	0.777
WF9_CHAR_HISP_999	-0.0027	1.136	-0.002	0.998	-2.229	2.224
WF9_CHAR_COUNTRY_BORN_2	-1.3943	0.751	-1.857	0.063	-2.866	0.077
WF9_CHAR_COUNTRY_BORN_3	-0.5024	0.311	-1.614	0.107	-1.113	0.108
WF9_CHAR_COUNTRY_BORN_999	-1.0408	1.214	-0.857	0.391	-3.421	1.339
WF9_CHAR_MARITAL_2	-0.0220	0.174	-0.126	0.899	-0.363	0.319
WF9_CHAR_MARITAL_3	-0.4347	0.388	-1.121	0.262	-1.194	0.325
WF9_CHAR_MARITAL_4	-0.1662	0.268	-0.621	0.535	-0.691	0.358
WF9_CHAR_MARITAL_999	-0.5470	1.205	-0.454	0.650	-2.910	1.816
WF9_CHAR_GOVT_PRGM_2	-0.1042	0.193	-0.538	0.590	-0.483	0.275
WF9_CHAR_GOVT_PRGM_999	0.2268	0.679	0.334	0.738	-1.104	1.557
WF9_CHAR_GENDER_2	0.4216	0.544	0.774	0.439	-0.645	1.489
WF9_CHAR_GENDER_999	0.4723	1.719	0.275	0.784	-2.898	3.842

WF9_C5_OVER4HR_TRAIN_1	-0.3081	0.214	-1.440	0.150	-0.727	0.111
WF9_C5_OVER4HR_TRAIN_2	0.1356	0.210	0.645	0.519	-0.277	0.548
WF9_C5_OVER4HR_TRAIN_3	-1.5003	1.195	-1.256	0.209	-3.842	0.842
CB9_SERVE_0TO3YRS_1	0.0445	0.194	0.229	0.819	-0.336	0.425
CB9_SERVE_0TO3YRS_999	1.0495	0.699	1.500	0.133	-0.321	2.420
WF9_PROFDEV_WRKSHP_2	-0.2892	0.183	-1.577	0.115	-0.648	0.070
WF9_PROFDEV_WRKSHP_999	1.4496	0.562	2.580	0.010	0.348	2.551
WF9_WORK_PLAN_2	0.1818	0.204	0.892	0.372	-0.218	0.581
WF9_WORK_PLAN_999	-76.3911	1.96e+16	-3.9e-15	1.000	-3.84e+16	3.84e+16
WF9_WORK_REVIEW_2	0.2079	0.161	1.294	0.196	-0.107	0.523
WF9_WORK_REVIEW_999	-0.4067	0.657	-0.619	0.536	-1.693	0.880
CB9_RVNU_CENTER_FUND_COMBO_2	-0.5469	0.298	-1.833	0.067	-1.132	0.038
CB9_RVNU_CENTER_FUND_COMBO_3	-0.2475	0.304	-0.813	0.416	-0.844	0.349
CB9_RVNU_CENTER_FUND_COMBO_4	-0.5282	0.247	-2.135	0.033	-1.013	-0.043
CB9_RVNU_CENTER_FUND_COMBO_5	-0.4771	0.320	-1.491	0.136	-1.104	0.150
CB9_RVNU_CENTER_FUND_COMBO_6	-0.1113	0.359	-0.310	0.756	-0.814	0.591
CB9_RVNU_CENTER_FUND_COMBO_7	-0.6934	0.274	-2.531	0.011	-1.230	-0.156
CB9_RVNU_CENTER_FUND_COMBO_8	-0.2355	0.201	-1.173	0.241	-0.629	0.158
WF9_CHAR_HEALTH_INSRNCE_2	0.3345	0.250	1.339	0.181	-0.155	0.824
WF9_CHAR_HEALTH_INSRNCE_3	0.3842	0.568	0.676	0.499	-0.730	1.498
WF9_CHAR_HEALTH_INSRNCE_4	0.0432	0.339	0.127	0.899	-0.621	0.708
WF9_CHAR_HEALTH_INSRNCE_5	-0.2378	0.309	-0.769	0.442	-0.844	0.368
WF9_CHAR_HEALTH_INSRNCE_6	0.4457	0.330	1.350	0.177	-0.201	1.093
WF9_CHAR_HEALTH_INSRNCE_7	0.3893	0.250	1.558	0.119	-0.100	0.879
WF9_CHAR_HEALTH_INSRNCE_8	0.2644	0.257	1.028	0.304	-0.240	0.769
WF9_CHAR_HEALTH_INSRNCE_999	0.2938	1.181	0.249	0.804	-2.022	2.609

Variable Descriptions

WF9_WORK_BEHAVIOR: Agreement to the statement “There were children with behavior problems that were hard to deal with,” where possible responses are:

1. Never
2. Once
3. More than once

WF9_WORK_RESPECT: Agreement to the statement “My co-workers and I are treated with respect on a day-to-day basis,” where possible responses are:

1. Agree
2. Neither agree nor disagree
3. Disagree
4. Strongly disagree:

WF9_WORK_PRNTS_TALK: Respondent's answer to the question "How often last week did you talk with a parent about something happening in the child's family (for example child-parent relationships, stresses like parent's finances and employment; family tensions)?" where possible responses are:

1. Not at all
2. Once or twice
3. Three or more times

WF9_ATTITUDES_PMS_PROG: Score on the Parental Modernity Scales - Progressive Belief Subscale. Considers respondent opinions on child obedience, interaction with authority, and appropriate child-parent relationships. Possible values of this variable range from 5 to 25, with 25 representing the most progressive beliefs.

WF9_WORK_YRS: Number of years respondent worked in the program.

WF9_WORK_HELP_AVAILABLE: Agreement to the statement, "I have help dealing with difficult children or parents," where possible responses are:

1. Strongly Agree
2. Agree
3. Neither Agree nor Disagree
4. Disagree
5. Strongly Disagree

Likelihood Factors

Below is a summary of variables with the highest level of significance. Likelihood factor refers to the predicted multiplied likelihood of depression that is associated with each unit increase (see above), holding all other variables constant.

Table 8: Statistically significant variables.

Variable Name	P-Value	Coefficient	Likelihood Factor
WF9_WORK_BEHAVIOR	0.000	.5724	1.77
WF9_WORK_RESPECT	0.000	0.4466	1.56
WF9_WORK_PRNTS_TALK	0.000	0.3518	1.422
WF9_ATTITUDES_PMS_PROG	0.000	0.1141	1.12
WF9_WORK_YRS	0.001	-0.0703	0.932
WF9_WORK_HELP_AVAILABLE	0.006	0.2001	1.22

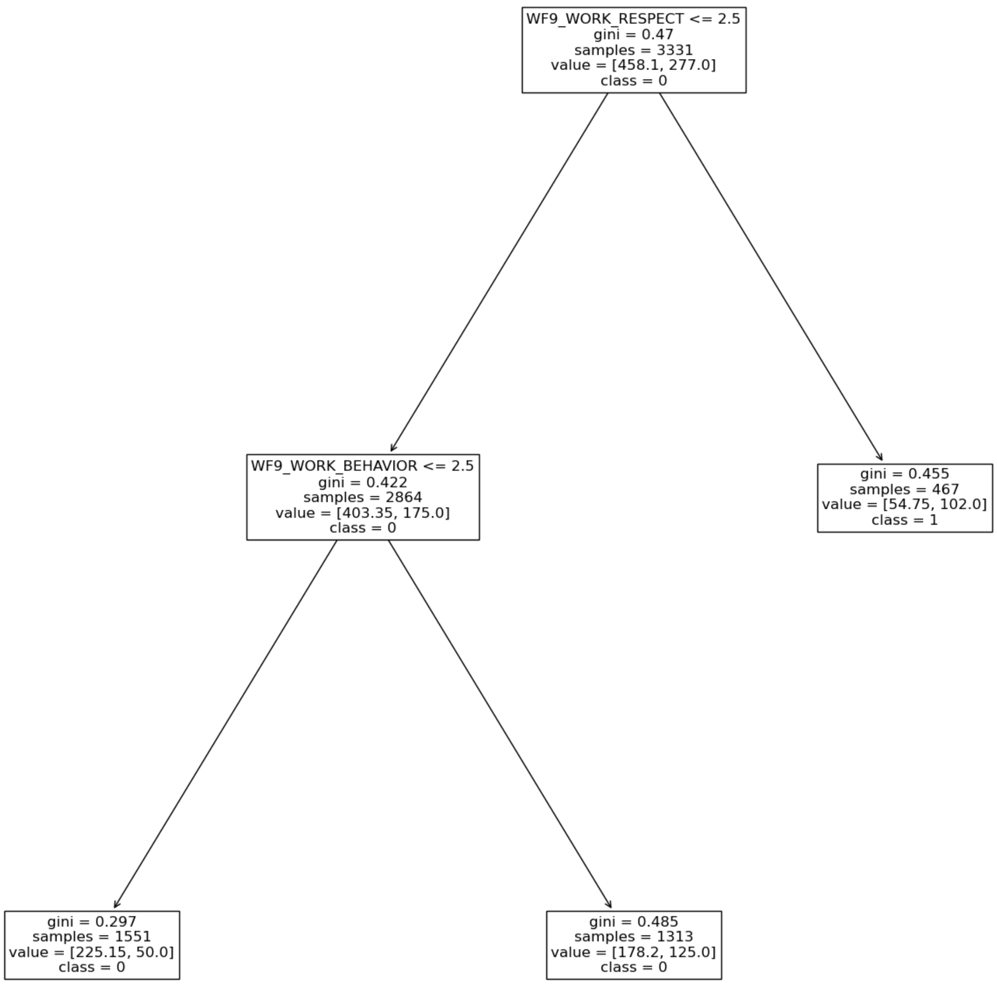
Feature Importance and Decision Trees

Table 9: CART and Random Forest performance.

	CART with Weighted Loss CV, W = 250	CART with F1 CV, Class_Weight = {0:0.14}	RF with Weighted Loss CV, W = 250	RF with F1 CV, Class_Weight = {0:0.14}
F1	0.095238	0.288889	NaN	0.321423
TPR	0.219512	0.433333	0.000000	0.219512
FPR	0.077720	0.121762	0.000000	0.015957
Precision	0.090909	0.216667	NaN	0.6
Accuracy	0.862981	0.846154	0.901679	0.908873

Considering both F1 score and TPR, the model whose performance surpassed most others was the CART classification model with Class Weight = {0: 0.14, 1: 0.86}, cross-validated to optimize F1 score. This model had an F1 score of 0.288 for the testing data. Given its relative efficacy, feature importance levels were analyzed to better understand the decisions being made. The model determined two variables - *WF9_WORK_RESPECT* and *WF9_WORK_BEHAVIOR* (in decreasing order) - to be important, while all others observed feature importance values of 0. These importances are reflected in the decision tree. The visualized decision tree reflects feature importance rates, with those most important features determining the initial splits and so forth. Given the visualized tree, it is clear to see that the model's decision to classify an observation as Class 1 is entirely dependent on the value of *WF9_WORK_RESPECT*.

Figure 6: Decision tree. Each tree node is labeled by the variable split (i.e. $WF9\_WORK\_RESPECT <= 2.5$) that informs the decision made by the classification model.



Next in performance was the Random Forest classifier with the same class weights as the CART model, with hyperparameters chosen through cross-validation to optimize F1 score. This model achieved an F1 score 0.32, but a comparatively much lower TPR. Here, the top three variables ranked by importance score were *WF9_WORK_RESPECT, WF9_WORK_BEHAVIOR,* and *WF9_ATTITUDES_PMS_PROG.*

Worst in performance were the CART and random forest models which were cross-validated on the custom loss function. The former had an F1 score of 0.07 on the testing data, only predicting two out of 30 positive cases. The latter did not predict any positive cases. The performance of the custom loss function in comparison to the other models suggests a potential error in defining the function itself. Future adjustments would need to be made in order to improve the performance of this model. Due to the low performance of the model, feature importance scores were not determined to be useful for this study's conclusions.

VII. Discussion of Results

The results of this study cannot establish any causal relationship between ECE working conditions and depression. In fact, none of the models succeeded in correctly identifying more than 50% of positive cases on the testing data, regardless of scoring metrics used during training or class weight manipulation. This indicates that the chosen variables in our training data do not explain the majority of variation within the dataset. Obviously, the causes of depression are deep and complex, and cannot be attributed simply to those variables accessible within the 2019 NSECE. The high imbalance within the dataset may also contribute to the inconsistencies in model prediction. Given the relative lack of respondents suspected of depressive disorder, it is difficult for models to accurately learn relevant patterns for prediction. In comparison to previous studies on childcare worker wellbeing, respondent depression rates within the NSECE data are much lower overall (possibly in part due to the survey's use of a truncated form of the survey). Thus, similar models may perform differently on these existing data which contain more relevant training points.

That said, we can identify patterns across the three modeling techniques that offer a glance at some of the key stressors for childcare workers. Certain variables consistently played an important role in models' ability to predict depression; out of the variables that had a statistically significant impact in the logistic regression model, two of them placed within the top two and six variable importance scores for the CART and Random Forest models, respectively - *WF9_WORK_RESPECT* and *WF9_WORK_BEHAVIOR.* We can thus consider these variables to be key predictors across multiple models, and key stressors for childcare workers' mental wellbeing. Again, these results merely highlight an interesting pattern; no causal relationship can be inferred from the results of this study

Perceived Respect at Work

WF9_WORK_RESPECT had the highest variable importance score in the CART classification model, and it also had the second greatest impact based on the logistic regression model - each one point increase as indicated by a worker's response is predicted to multiply the relative likelihood of depression by 1.585.

As suggested by these results, respondents' perceived treatment by those around them had an important impact on their wellbeing. This finding is consistent with past literature on childcare workers' wellbeing, which has indicated that a lack of respect as professionals is a core contributor to workers' high levels of mental and emotional stress. Perceived often as simply "babysitters," childcare workers are consistently devalued and denied appropriate respect or compensation for their difficult work. As many studies and focus groups have noted, these perceptions contribute to the mentally draining nature of ECE work.

Children's Behavior at Work

WF9_WORK_BEHAVIOR had the highest impact on the logistic regression model's predictions - each increase in frequency as indicated by a worker's response, is predicted to multiply the relative likelihood of depression by 1.79. *WF9_WORK_BEHAVIOR* also had the second highest variable importance score in both CART and Random Forest models.

These results suggest that childcare workers' mental wellbeing is highly impacted by the children that they care for. Of course, this impact is understandable - caring for children with difficult behavioral problems can reasonably cause high levels of emotional and even physical distress. These findings support the conclusions and recommendations of Otten et al. regarding the importance of "current efforts to invest in mental health consultants to work with teachers, directors, and parents to develop strategies to help children who are struggling with behavioral problems."[39] That is, one tangible possibility for improving the mental wellbeing of childcare workers is an improved access to resources that facilitate engaged, healthy relationships with all children in their care.

Other Significant Variables

In addition to *WF9_WORK_RESPECT* and *WF9_WORK_BEHAVIOR,* a few other variables were significant across multiple models. *WF_WORK_HELP_AVAILABLE, WF9_ATTITUDES_PMS_PROG,* and *WF9_WORK_YRS* all had high statistical significance in the logistic regression model, and remained within the top six most significant variables for the Random Forest model. These results suggest that a respondent's level of experience at their job and the level of progressivity with which they interact with children may have an association with their mental health. In particular, the results of the logistic regression suggest that increased work experience is associated with a lower likelihood of depression, while increased progressivity in caregiving attitudes is associated with a higher one. The latter observation is interesting and not necessarily intuitive, calling for further research on the topic. Additionally, the role of *WF_WORK_HELP_AVAILABLE,* is particularly interesting, because it can be understood as a response to the feature *WF9_WORK_BEHAVIOR.* That is, if children do frequently misbehave at work, a respondent's access to support in dealing with this behavior also seems to be somewhat predictive of mental wellbeing.

Overall Picture

The results of this study find solely work environment-related variables to offer any glimpse at the mental wellbeing of childcare workers - all other features appear insignificant. Like Jeon et al., this study found no strong evidence of any effect of professional background (such as education), most demographic covariates, or wages on depression. The latter is particularly interesting within the context of recent literature; while a great deal of research has suggested compensation to be an influencing factor in mental wellbeing, a

[39] Otten, Jennifer L., 718.

2015 study on HeadStart staff similarly found salary to be non-significant indicator of teacher wellbeing.[40] Despite the uncertain conclusions of this study, the inferences made align closely with many of the findings of Jeon et al.. In particular, their study found that positive perceptions of teachers' work environment was associated with positive mental health, while "childcare chaos" and children's behavior were more significant predictors of depression, exhaustion, and stress.[41]

Combining the results of the models, a picture begins to emerge about the working environment of childcare workers as it relates to mental health; when the responsibilities of childcare workers become particularly draining due to the children they care for, their mental health suffers. Their stress is particularly compounded when workers do not have access to support systems which can alleviate these client-caused difficulties. Above all, the respect that childcare workers believe they receive is the greatest indicator of their mental wellbeing - when childcare workers do not feel respected for the work that they do, they may be as much as 1.5x more likely to exhibit signs of depression, holding all other variables constant. In conjunction, these results emphasize the importance of a positive and supportive working environment for childcare worker mental wellbeing.

VIII. Conclusion

While the results of this study do not support the initial hypothesis that financial and structural components would contribute to depression levels, they offer an important look at the mentally draining work environment that many childcare workers face. More than wages, income, or demographic characteristics, it seems to primarily be the everyday working environment that influences the mental health and depression of workers. Indeed, the results would suggest that by simply respecting and valuing childcare workers we may improve their mental health significantly. This conclusion points to two important shifts that must take place: first, we must see a change in cultural attitudes towards childcare workers past their role as "babysitters" and

[40] Wells, Michael B. "Predicting Preschool Teacher Retention and Turnover in Newly Hired Head Start Teachers Across the First Half of the School Year." Early childhood research quarterly 30.Pt. A (2015): 152–159. Web.

[41] Jeon, Lieny et al., 68.

instead as crucial, skilled workers. By fostering an environment of support, advocacy, and respect, we can help to protect this vital workforce in our society. Second, childcare centers need more support and resources in place for workers, especially when dealing with client problems and a lack of respect. These resources may be in the form of psychological or therapy-based support, improved child-to-teacher ratios, better-informed strategies for conflict management, and many others. Of course, childcare centers cannot provide this support while they continue to be underfunded, understaffed, and under-resourced. Thus, this change must entail broader shifts in ECE policy (on local, state, and federal levels) that better prioritizes the funding and support of ECE centers and providers. While these changes may be difficult to achieve, they are essential to ensuring the health and wellness of this critical workforce in our nation.

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