Predicting Material Hardship: The Role of Life Satisfaction

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1 Introduction

Understanding key contributing factors to life outcomes for vulnerable populations can be critical to inform policy interventions. However, policymaking often lacks evidence-based decision-making and rarely involves mass collaboration (Salganik et al., 2020). The Fragile Families Challenge represented a novel initiative in social science research, promoting mass machine learning collaboration to predict life outcomes for families in the Fragile Families and Child Well-Being Study (FFCWS) (Salganik et al., 2020). The study involved longitudinal data from a birth cohort study of children born between 1998 and 2000 focusing on aspects such as children's educational achievements, family economic stability, and health (Thomas, 2022). Participants in the challenge were provided a standardized set of background variables from the FFCWS data and were tasked with tasked with creating predictive machine learning models for six key outcomes: child grade point average (GPA), child grit, household material hardship, household eviction, primary caregiver layoff, and primary caregiver participation in job training.

While the challenge was focused on finding optimal predictive models, the vast dataset combined with machine learning approaches also provides a fruitful opportunity to examine specific key predictors of vulnerable family outcomes. Material hardship is particularly important to understand as predicting economic deprivation can be essential to improve the lives of families in precarious situations.

Specifically, it provides a nuanced view of economic struggles and the ability of households to meet their needs (Nelson, 2011). Meanwhile, subjective well-being (SWB) has been shown to reflect many individual factors and is associated with children's life outcomes and economic hardship (Haines & Grimes, 2022). It is also measured for all waves of the FFCWS data as life satisfaction. With a focus on child and family well-being, this study seeks to uncover the predictive potential of subjective well-being for future material hardship.

Several studies have analyzed material hardship using the FFCWS data. This includes papers aiming to maximize the predictive power of models or examining longitudinal patterns of material hardship (Thomas, 2022; Altschul, 2019; McKay, 2019). Several studies have already found past material hardship to be a strong predictor (Altschul, 2019; McKay, 2019). Another analysis focused on child conduct and behavior as a result of family material hardship (Zilanawala & Pilkauskas, 2012). However, this is the first study to my knowledge to analyze the predictive power of subjective well-being for material hardship using machine learning approaches on the FFCWS data.

1.1 Material Hardship

Measuring economic deprivation must go beyond simple measures such as income, as this fails to account for varied hardships like food insecurity, housing instability, and inadequate healthcare (Shelleby, 2018). A multi-dimensional measure such as material hardship is more comprehensive as it measures how families experience deprivation and whether their needs are met (Edmunds & Alcaraz, 2021; Heflin, 2014, 2016). Material hardship is defined by Nelson (2011, p. 1) as "an inadequate consumption of goods or services that the public deems minimally necessary for decent human functioning." Following this definition, she found that being hardship poor was more widespread in the U.S. than official poverty rates.

Indeed, families can have heterogeneous experiences of deprivation even at similar income levels (Edmunds & Alcaraz, 2021; Dhongde & Haveman, 2017; Mayer &

Jencks, 1989). Moreover, both those above and below the poverty line can experience material hardship (Edmunds & Alcaraz, 2021; Dhongde & Haveman, 2017). Additionally, populations typically viewed as economically secure can experience hardship at levels closer to those of traditionally disadvantaged groups (Nelson, 2011). Dhongde and Haveman (2017) also found higher rates of multidimensional deprivation than official poverty rates, with the most deprivation seen for housing, education and health insurance. Material hardship therefore provides a more comprehensive assessment of the pressures families endure. The consequences of childhood economic hardship are extensive, with affected children more likely to suffer from mental health issues and, as adults, to achieve lower levels of education, earn less, and have worse health outcomes (Shelleby, 2018; Reiss, 2013; Duncan et al., 2010).

The Fragile Families and Child Well-Being Study (FFCWS) uses material hardship to measure extreme poverty. The scale used was introduced by Mayer and Jencks (1989). It was subsequently used in the federal Survey of Income and Program Participation (SIPP) and was adopted in the FFCWS (Lundberg, 2017). According to Thomas (2022), it is also the only dataset to provide several measures of material hardship in various years on a national scale. The study therefore offers valuable longitudinal data to assess predictors of multi-dimensional material hardship.

1.2 Life Satisfaction

Life satisfaction is often used to measure SWB and represent overall well-being (Haines & Grimes, 2022). Notably, it has been validated as a stable and consistent measure across time and different contexts (Diener et al., 2013). Increasingly, organizations and leaders promote it as an important metric that transcends traditional economic measures such as GDP and provides a more holistic view of a population's well-being (Layard, 2010). A major advancement was the Stiglitz report, produced by a commission established by President Sarkozy to promote the measurement of subjective well-being (Stiglitz et al., 2009). International SWB measurement efforts include the OECD's Better Life Index, the World Happiness Report, and the UN Human Development Index. National governments, such as the United Kingdom, France, Germany, and New Zealand, have also declared it as a policy goal (Frey & Gallus, 2013; Haines & Grimes, 2022). Layard (2010) recommends that it should be measured in all surveys to identify what is important for people's well-being and appropriately adjust societal priorities. This can facilitate trend monitoring, distinguish vulnerable groups, and identify influencing factors (Layard, 2010). SWB also provides a more holistic evaluation of policy impacts (Layard, 2010).

A notable body of research has focused on the relationship between SWB and economic situation. Higher income is associated with higher SWB, though the relationship is not linear and historically studies found weaker than expected relationships (Christoph, 2010; Frey & Gallus, 2013). Subsequent research has examined this relationship and found that when more comprehensive deprivation measures are used, they can explain more of the variance in subjective well-being (Christoph, 2010). Life satisfaction and satisfaction with family life have also found to be significantly associated with economic hardship (Blom et al., 2019; Sabella & Suchan, 2019). Further, Lewin et al. (2023) found that material hardship had a negative effect on emotional well-being, and Heflin (2009) found a strong relationship between material hardship and depression. Moreover, Carver and Grimes (2019) found that consumption-based measures were a better predictor of subjective well-being than income.

SWB has been recommended as an important measure of focus above other domains of overall well-being, as it incorporates many individual factors (Smith, 2018; Haines & Grimes, 2022). While well-being is multi-faceted and more multidimensional indices of well-being have been proposed (OECD, 2011), life satisfaction has been found to be positively associated with other measures of well-being including health and migration choices (Deaton, 2008; Grimes et al., 2012; Grimes & Wesselbaum, 2019; Haines & Grimes, 2022). SWB can lead to a number of positive outcomes such as better economic performance, productivity, and physical health (Howell et al., 2016).

Moreover, parents' and particularly mothers' health and well-being are strongly related to their children's well-being and future life prospects (Dominick, 2018; McLoyd, 1998; Conger et al., 2002; Haines & Grimes, 2022). This can have a significant impact on child outcomes as stress from financial difficulties can impact the mental health of parents, parental conflict, and child-parent conflict and interactions (Jaffee & Poulton, 2006; McLoyd, 1998; Dominick, 2018; Conger et al., 2002; Haines & Grimes, 2022). This can have substantial implications for the child's well-being as their socioemotional and academic abilities can be impacted (Haines & Grimes, 2022). Dominick (2018) found that material hardship was significantly associated with higher probability of maternal depression and anxiety, which had a negative influence on child temperament by 9 months. Additionally, McLeod (2018) found that single parents, particularly those from marginalized groups, had lower levels of well-being and were more likely to experience material hardship.

I therefore seek to explore the predictive power of life satisfaction, a measure of subjective well-being, for material hardship outcomes. I hypothesize that mother's life satisfaction will be a strong predictor for this particular outcome given the influence of mothers on child outcomes, the relationship between multidimensional economic hardship and well-being, and the idea that life satisfaction may reflect many factors related to personal experiences and economic hardship. In particular, I predict that higher life satisfaction will predict lower material hardship, and vice versa.

2 Methods

2.1 Dataset

The Fragile Families dataset is representative of all U.S. cities with populations greater than 200,000 in 1998 and contains thousands of variables about social and financial situation, demographics/identities, and relationships (Thomas, 2022). It initially involved 4900 families and includes surveys conducted at ages 1, 3, 5, 9, and 15 (Reichman et al., 2001). The final survey wave retained approximately 3600 families. It particularly involved families in vulnerable circumstances, with 75% of the families having unmarried parents (Thomas, 2022).

Table A.1 presents the questions in the survey related to material hardship. They are asked in every wave excluding the baseline and ask about the past 12 months. The final metric is calculated by the proportion of the questions for which the caregiver answered yes. Thus, the measure ranges from 0, or less material hardship, to 1, more material hardship (Lundberg, 2017).

2.2 Data Cleaning

As the original dataset contains a large amount of missing values, I performed several steps to prepare the data. I first dropped any columns that had more than 70% missing values, as well as any with low variance (less than .05) to remove columns that would not have much influence. I further removed any columns that were categorized as paradata and weights or were identifier columns. This reduced the dataset from 12,943 to 4,247 features.

I then conducted mean imputation for continuous and ordered categorical variables and mode imputation for binary or unordered categorical variables. Though more involved imputation methods have been attempted for model optimization, prior efforts found that simpler methods such as mean imputation did not perform much worse than complex methods (Ahearn & Brand, 2019; Filippova et al., 2019; Salganik et al., 2019; Stanescu et al., 2019).

Following other studies on material hardship, I chose not to impute missing values for the outcome variable as non-response is likely not random (Thomas, 2022; Zilanawala & Pilkauskas, 2012). Imputing the data could introduce a bias given the unknowns for which the material hardship questions were not answered. While this may exclude those that are more marginalized as they are less likely to respond to the survey, the best practice in these studies avoids introducing bias from imputing missing data (Stavseth et al., 2019; Thomas, 2022; White & Carlin, 2010). From the provided training dataset of 2,121 families, this leaves 1,459 with reported material hardship.

2.3 Descriptive Statistics

Figure 1 shows the distribution of the material hardship outcome data at age 15. It is skewed with most falling on the lower end of the material hardship scale. As reported in Table 1, over 50% reported no material hardship at all, while the maximum material hardship reported was 0.82.

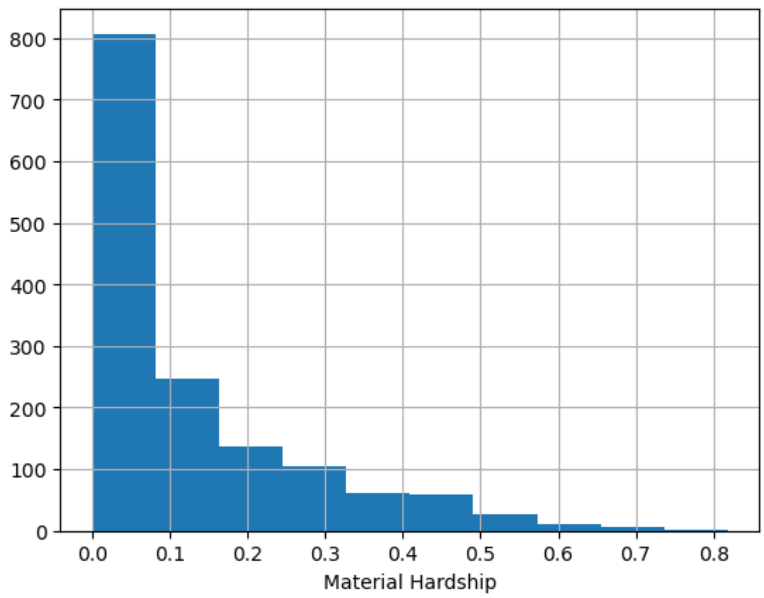

Figure 1: Material Hardship Training Data Distribution

To measure life satisfaction, the survey asks how satisfied mothers and fathers feel with their life overall at each wave, with 1 being very satisfied and 4 being very dissatisfied. Figure 2 shows the correlations of this question to material hardship at age 15. The highest correlation (0.26) is the mother's life satisfaction at year 9.

Figure 3 shows the distribution of mother's life satisfaction at year 9. This data is also skewed with the majority reporting high life satisfaction. The distribution of

	materialHardship
count	1459.00
mean	0.10
std	0.16
min	0.00
25%	0.00
50%	0.00
75%	0.18
max	0.82

Table 1: Descriptive Statistics of Material Hardship Measure at Year 15

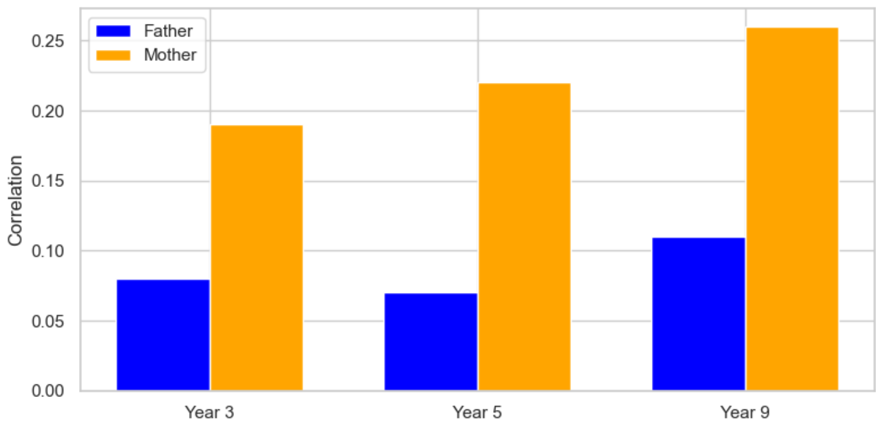

Figure 2: Correlation of Life Satisfaction with Material Hardship at Age 15

the prepared and imputed data aligns with that of the original data provided (see Figure 4). Table 2 lists the possible answers to the life satisfaction question and the frequency for each answer in the mother survey at age 9, as reported by the FFCWS metadata (*FFCWS Metadata*, n.d.). The majority of the missing data is because the respondent was not in the wave.

Value	**Label**	**Frequency**	**Percent**
1	Very satisfied	1434	29.28
2	Somewhat satisfied	1679	34.28
3	Somewhat dissatisfied	317	6.47
4	Very dissatisfied	83	1.69
-9	Not in wave	1383	28.24
-2	Don't know	1	0.02
-1	Refuse	1	0.02

Table 2: Life Satisfaction Responses. Source: FFCWS Metadata

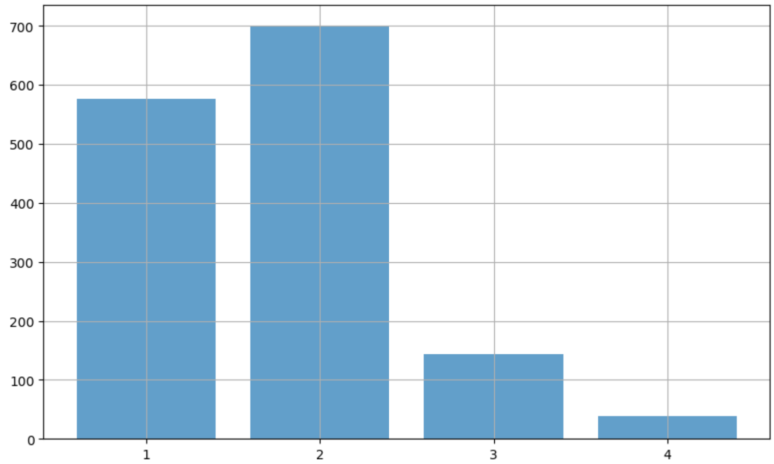

Figure 3: Life Satisfaction Prepared Data Distribution

2.4 Model Selection

2.4.1 LASSO

To select an appropriate model for the prediction, I ran several baseline models on the remaining features from the prepared data and assessed their performance.

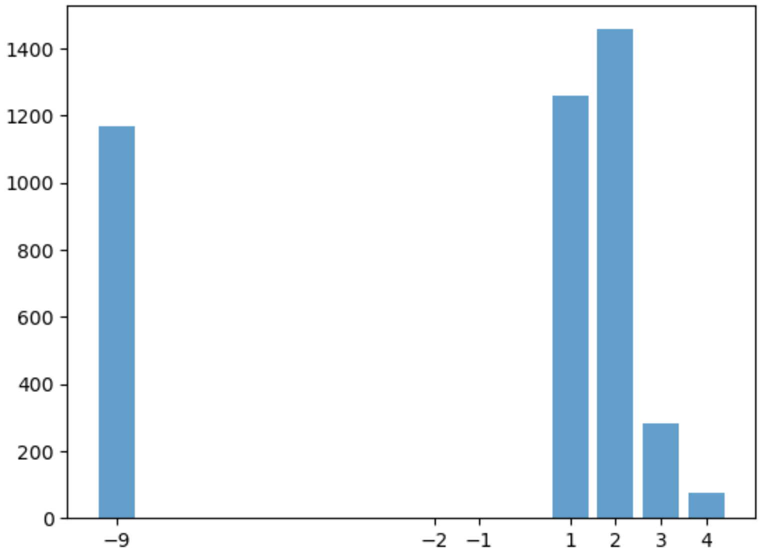

Figure 4: Life Satisfaction Original Data Distribution

I then selected two models, LASSO and random forest, for further analysis and interpretation.

Salganik (2019) discusses the usefulness of regularized regression and LASSO as follows. Building on the Ordinary Least Squares (OLS) loss function, LASSO adds a regularization component as a penalty term. It uses the absolute value of the coefficients and helps address overfitting by minimizing select coefficients to zero. For high-dimensional datasets such as the Fragile Families dataset, this is useful for feature selection to narrow down the number of predictors, reduce complexity, and improve out-of-sample performance (Salganik et al., 2019). This helps make the model more interpretable and focuses the analysis on the most relevant predictors to help answer the research question. Therefore, given the wide dataset and the primary focus on analyzing important features, I used LASSO to select important features for material hardship. I opted for automatic variable selection as prior efforts found that manual variable selection did not produce substantial improvements in predictive power (Filippova et al., 2019; Roberts, 2019; Salganik et al., 2019).

The parameter λ, or alpha, controls the strength of the regularization and can improve out-of-sample performance by reducing susceptibility to noise (Salganik et al., 2019). A larger alpha results in a larger penalty for the coefficients; thus, there is a tradeoff between a lower alpha and overfitting (Filippova et al., 2019). The hyperparameter was chosen using cross-validation with five folds. In cross-validation, the data is randomly split into k folds and the model is fit on all but one fold. The left-out fold acts as the validation set to assess performance. Thus, it can find the best hyperparameter by selecting the one that obtains the lowest cross-validation mean squared error (MSE). The average MSE across folds can also estimate how the model will perform out-of-sample (Salganik et al., 2019). Within the cross-validation pipeline, I standardized the data at each cross-validation step using StandardScaler from scikit-learn to prevent any data leakage and ensure the same transformation from the training data was applied to the validation and test data.

2.4.2 Random Forest

I also chose to evaluate a random forest model for a comparison with a more complex, tree-based model. The random forest model differs from LASSO as it does not assume a linear relationship and can naturally introduce non-linearities (Salganik et al., 2019). In a dataset such as Fragile Families, variable relationships can be complex and non-linear, making this a well-suited model.

Salganik et al. (2019) also discussed the relevance of tree-based methods and random forest models for the Fragile Families Challenge. Random forest reduces the estimation variance by averaging over a large number of different trees, each built on a bootstrap sample of the data and a random subset of features. This ensemble approach minimizes the risk of single trees where the model can be overly sensitive to the training data, thus enhancing robustness (Salganik et al., 2019). This is particularly valuable in an application aiming to predict consequential outcomes on unseen data for vulnerable families. Several top performing models to the Fragile Families Challenge used this approach (Compton, 2019; McKay, 2019; Rigobon et al., 2019).

To choose hyperparameters for the random forest and find the best performing model for each outcome, I again conducted five-fold cross-validation, tuning parameters to optimize mean squared error (MSE). I employed both a grid search and random search to tune the hyperparameters within each fold.

The choice of LASSO and random forest for analyzing the Fragile Families dataset leverages the strengths of both regularization and tree-based ensemble methods. LASSO can perform interpretable variable selection and reduce overfitting, while random forest can robustly capture complex patterns in the data. I employed both models to analyze predictions and important features for material hardship. To predict the other five outcomes, I used the random forest model for its ability to capture non-linearities and its applicability to both continuous and binary outcomes.

3 Results

3.1 Baseline Models

Table 3 displays the performance of several models on the remaining features after data cleaning for a validation and holdout test set. The LASSO model was the top performing model, while the XGBoost and random forest models had similar performance as the next best models. These all performed far better than the simpler linear (OLS) and decision tree models, which had the highest MSE. I chose to use the LASSO model for subsequent analyses given its high performance and interpretability. I also chose to use the random forest model given its higher performance along with the goal of choosing a model that is relatively straightforward but allows for non-linearities. This model can be more easily understood and interpreted than boosting models such as Gradient Boosting and XGBoost and had similar or better performance. Moreover, it was more efficient and requires less tuning to avoid overfitting than XGBoost (Gupta, 2021; Wohlwend, 2023).

	Linear	LASSO	Decision Tree	GBM
Validation MSE	0.0277	0.0192	0.0422	0.0216
Test MSE	0.0307	0.0232	0.0444	0.0248

	XGBoost	Random Forest
Validation MSE	0.0194	0.0199
Test MSE	0.0239	0.0239

Table 3: Model Performance

3.2 LASSO Feature Selection

The LASSO model resulted in 52 features with a non-zero coefficient. Table A.2 lists the top ten features selected by LASSO with the respondent, subtopics, and wave. The top feature was "How satisfied you are with your life overall" asked to the mother in year 9. Figure 5 shows the number of features selected by survey respondent. The questions answered by the mother were the most influential, followed by the primary caregiver. Figure 6 also shows that the largest amount of important features came from Year 9. However, Year 3 had more selected features than Year 5. Figure 7 displays the features by subtopic. The top two feature subtopics were material hardship and behavior by a substantial amount.

After obtaining the most influential features from the baseline model, I ran the LASSO and random forest models using the selected 52 features, performing cross-validation and hyperparameter optimization. The final hyperparameters selected from the random search can be found in Table A.3. As seen in Table 4, the random forest model had the best performance on the held out test set.

Model	MSE
LASSO with Selected Features	0.0251
Random Forest with Selected Features	0.0234

Table 4: Feature Selection Model Performance

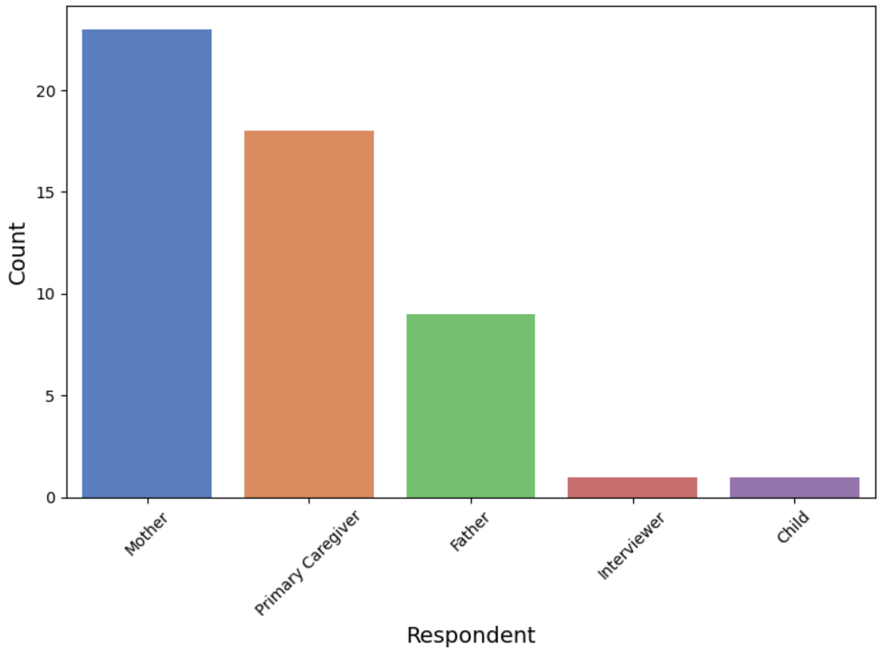

Figure 5: Count of Top Features by Survey Respondent

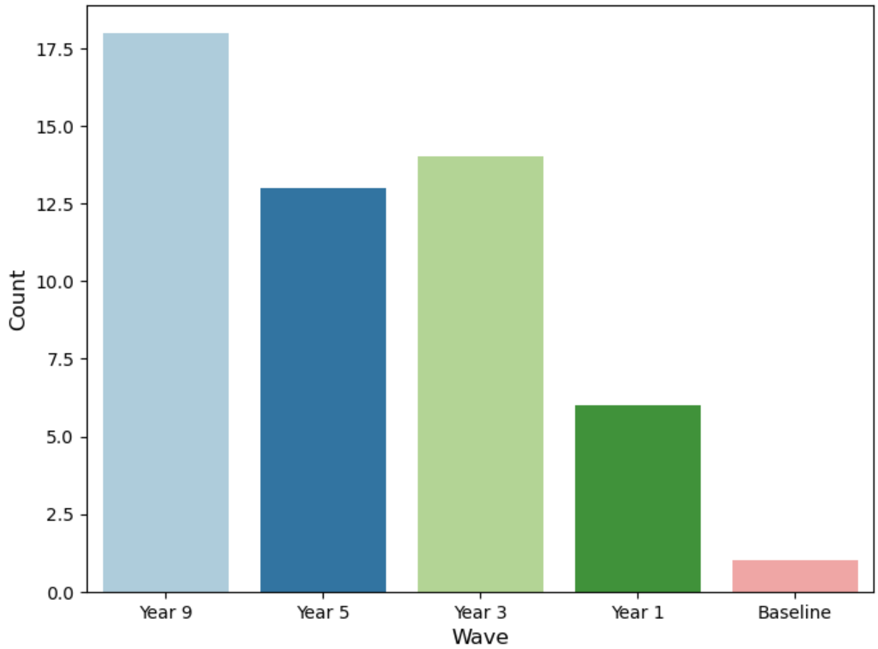

Figure 6: Count of Top Features by Wave

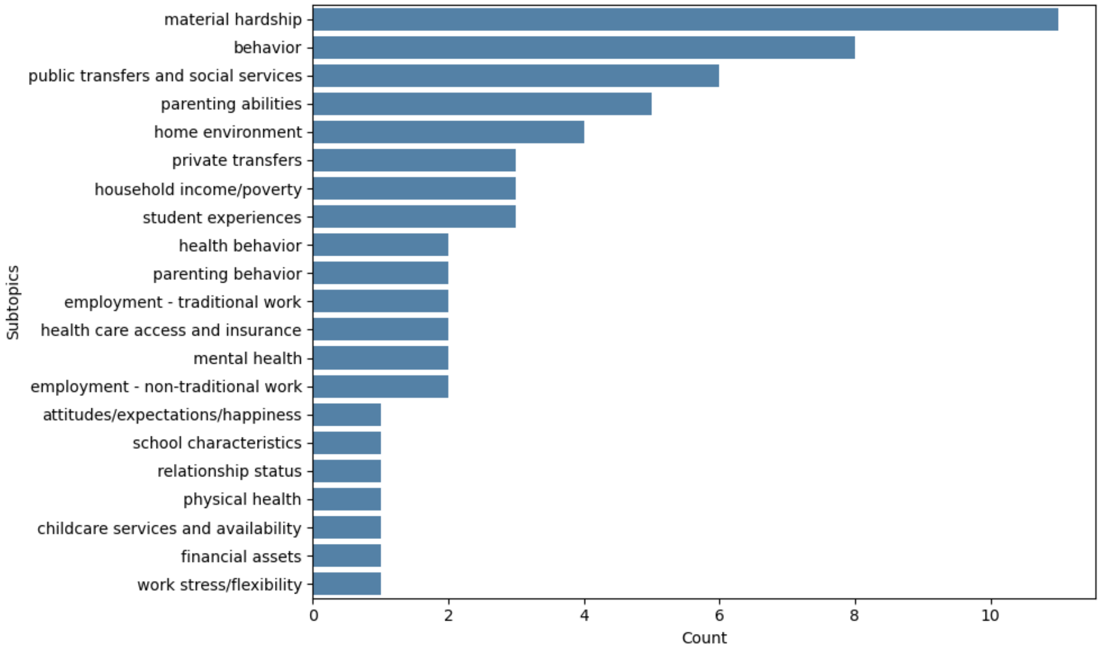

Figure 7: Count of Top Feature Subtopics

3.3 Model Interpretation

While individual decision trees can be easily interpreted by following the decisions of the tree, an ensemble model with multiple trees becomes less interpretable. The rationale for the output is less clear and it is not as easy to see the most influential predictors (McKay, 2019). Therefore, model interpretation techniques are useful to understand the influence of different variables. First, measures of variable importance are available to address this. They replace each variable with a randomized version and compare the difference in accuracy of the model (McKay, 2019). Thus, a variable is important if the accuracy drops with the randomized version.

I cross-examined the LASSO selected features with the top important features from the random forest model. Table A.4 lists the top ten features from the random forest feature importance. Both the random forest and the LASSO model found mother's life satisfaction at year 9 to be the strongest predictor. Further, both models' top four features were from Year 9, and nine out of the top ten features were from the mother. Additionally, eight out of the top ten features for both models were from the material hardship or poverty subcategory.

Partial dependence plots (PDP) are another tool for model interpretation and offer a model agnostic technique. They marginalize or average out the effect of other variables to show the marginal effect of a variable on the prediction function (Molnar, 2022). Figure 8 shows the PDP for the random forest model with all variables. As life dissatisfaction increases, predicted material hardship increases until the feature's score reaches 3. After this level of dissatisfaction, it has a minimal effect. Meanwhile, for the Random Forest model with LASSO-selected features, life dissatisfaction consistently has a positive marginal effect on predicted material hardship (see Figure 9).

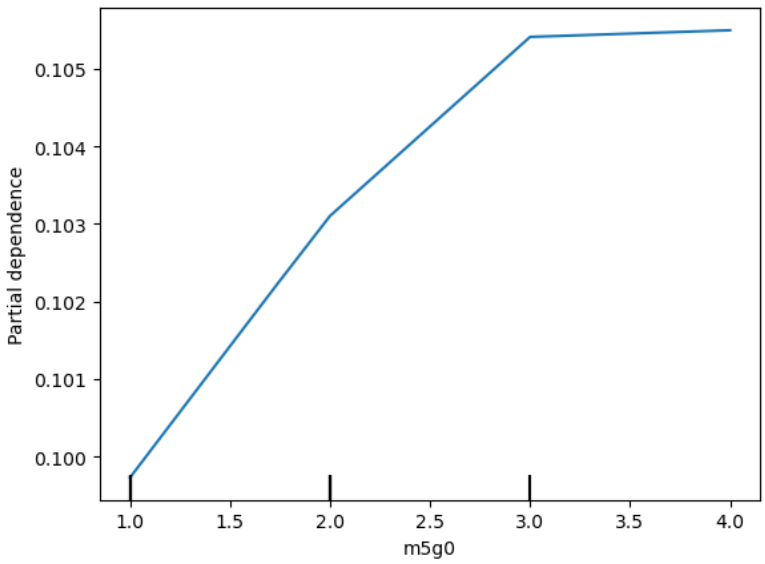

Figure 8: Life Dissatisfaction Partial Dependence (Random Forest Model)

Shapley values provide a modern model interpretation technique. Drawing from game theory, they look at all coalitions of variables to measure the marginal effect of a particular variable of interest for a sample (Molnar, 2022; Shapley, 1953). They then average all the effects on the prediction when compared to all other possible coalitions of variables. SHAP (SHapley Additive exPlanations) is based

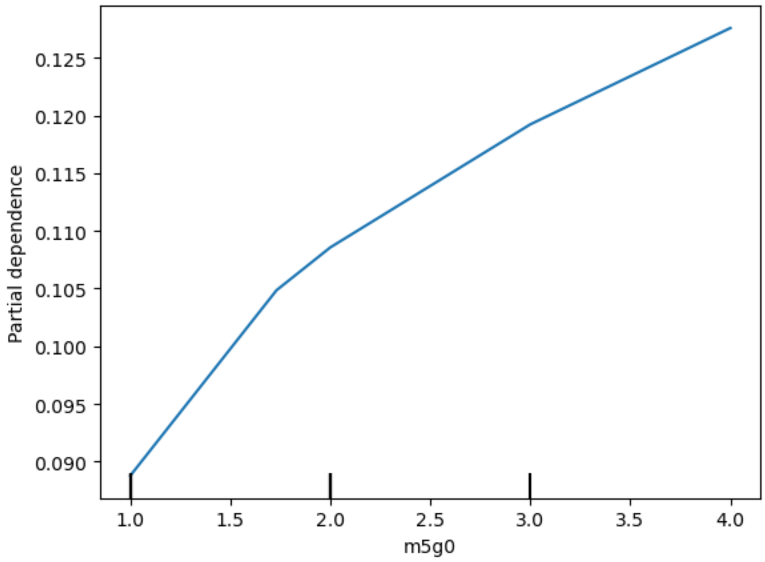

Figure 9: Life Dissatisfaction Partial Dependence (Random Forest with Selected Features)

on Shapley values and provides interpretation for individual predictions by calculating each feature's contribution (Molnar, 2022). It provides the explanation as a linear model of feature contributions, which connects Shapley values to LIME (Local Interpretable Model-agnostic Explanations), another interpretation method using local surrogate models (Molnar, 2022). I specifically employed TreeSHAP, which was proposed for tree-based models and more efficiently computes SHAP values (Molnar, 2022). The SHAP Summary Plot shows the feature values for a particular data point and what the effect was on the prediction value. For example, a low 'm5g0' (life dissatisfaction) had a negative effect on predicted material hardship with a larger magnitude than the majority of the other features. The dense clustering of dots for a medium value of life satisfaction suggests a strong consistent impact of this value on the model's material hardship predictions across many samples. Features like 'm5f23e', 'm5g0', and 'm5f23g' have a more substantial impact on the model's predictions compared to others at the bottom of the plot, such as 'p5q3g', whose SHAP values are closer to zero.

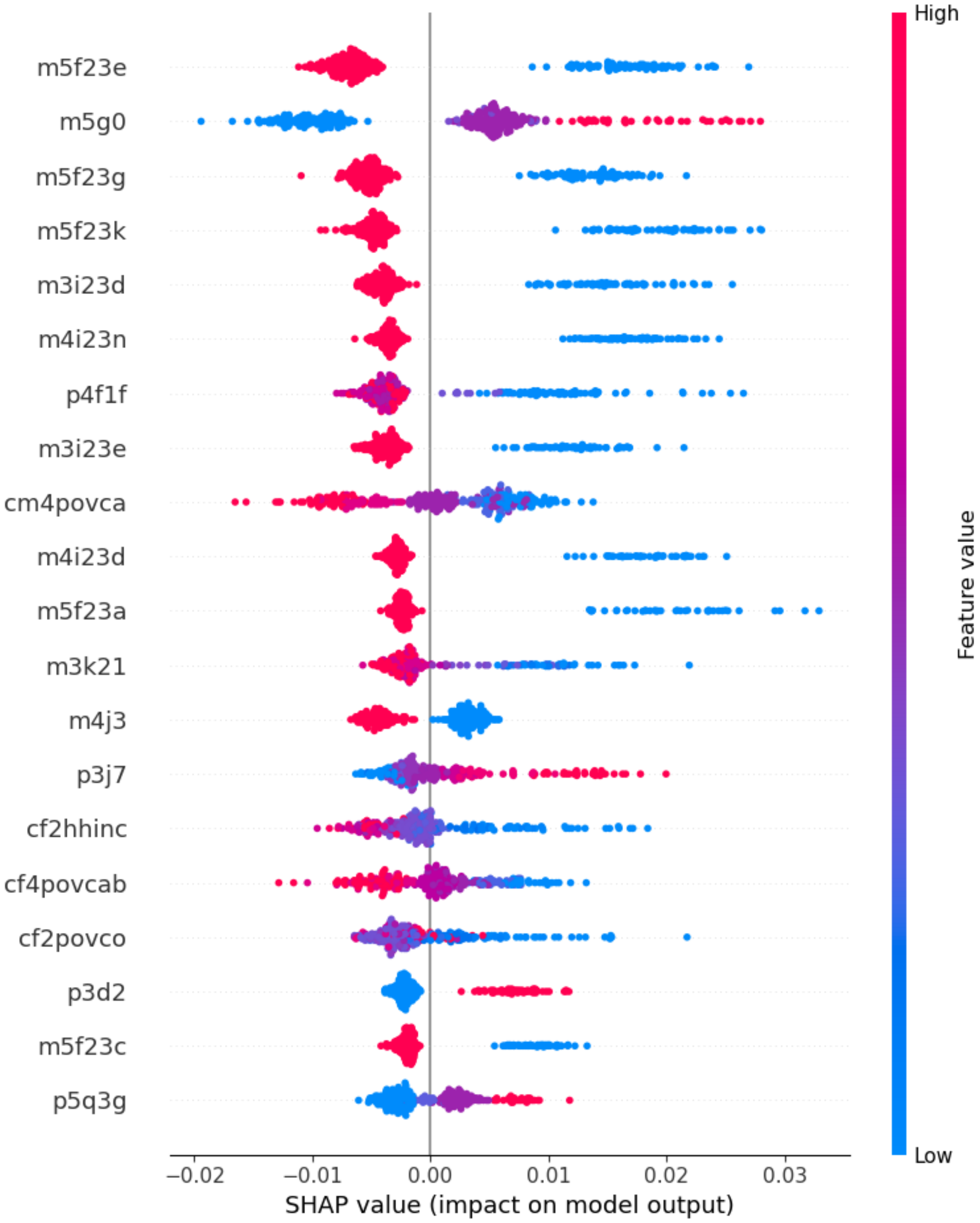

Figure 10: SHAP Summary Plot for Material Hardship Random Forest Model

3.4 Outcome Model Performance

I also ran the random forest model to predict the other five outcomes from the Fragile Families Challenge. For the binary outcomes, the classes were highly imbalanced. Therefore, I upsampled the data prior to training the model. I chose to randomly upsample the minority class as the counts for the minority classes were very small. I also ran LASSO for feature selection, which produced a small improvement on the test MSE. Table 5 shows the holdout set model performance for all six outcomes.

	gpa	grit	eviction	jobTraining	layoff	materialHardship
Test MSE	0.3837	0.2371	0.0514	0.2457	0.1758	0.0232

Table 5: Final Model Performance for All Six Outcomes

4 Discussion

Utilizing machine learning approaches to interpret models and understand key predictors, rather than merely maximizing predictive power, offers a valuable method to gain insights into vulnerable family outcomes. The findings show strong evidence for life satisfaction as a predictor of material hardship. The high correlation between mother's life satisfaction to material hardship at year 15 provided initial evidence that mother's past life satisfaction can be linked to future material hardship. Meanwhile, the father's life satisfaction does not appear to be strongly linked, aligning with past findings that mothers' experiences are more influential than fathers' (Stanescu et al., 2019).

The LASSO and random forest models permitted the analysis of influential features predicting material hardship. Again, the features selected by LASSO were primarily responses from the mother or primary caregiver, while the father's responses were far less important. Notably, life satisfaction emerged as the most important feature for both the LASSO and random forest, underscoring its consistent relevance across different models in predicting material hardship.

The SHAP summary plot shows mother's life satisfaction at year 9 was the second most important after bill-paying hardship. Low dissatisfaction had some of the strongest negative impacts on material hardship prediction, while higher dissatisfaction was more varied but consistently predicted increased material hardship. The Partial Dependence Plot in Figure 8 shows that when all variables are included, life satisfaction is no longer influential after 3.0. In other words, the "very dissatisfied" response was not as influential as responses reporting more life satisfaction. This may be because only 1.7% of respondents reported being very dissatisfied and other variables marginalized its effect.

Additionally, another top ten feature for the LASSO model was the question "There are quite a few things that bother you about your life", while the feature "You are less interested in people than you used to be" ranked highly in the random forest model. These two features, falling under the parenting abilities subtopic, also relate to the primary caregiver's life attitudes and subjective well-being. "There are quite a few things that bother you about your life", or 'p4f1f' was also the seventh feature listed on the SHAP Summary plot with a distinct split between high and low values on their prediction. The answers ranged from 1 (strongly agree) to 4 (disagree). Strong agreement to this question had a varied but positive, sometimes strong impact on material hardship prediction. Both 'm5g0' and 'p4f1f' had some of the SHAP values with the highest impact out of all the variables shown. These are the only features not from the material hardship or poverty subtopic in the top 10 features for either model. Bill-paying hardship ('m5f23e' and 'm5f23g') also emerged as particularly important variables across all model interpretation methods. This first validates previous findings that prior material hardship outcomes are strong predictors for future outcomes (Stanescu et al., 2019). It further adds to the literature by showing that variables relating to life satisfaction emerge as an additional category of important predictors.

5 Limitations

While the machine learning models revealed several important insights, the analysis has several limitations to consider. First, the levels of material hardship may be underestimating actual material hardship experienced by all families in the study as missing values of material hardship were excluded. The missing values likely represented more marginalized families, and thus the results may represent lower material hardship than that of all families in the study.

Generally, the dropping and imputation of missing values could have an effect on the results, though previous efforts showed that more complex imputation efforts did not show substantial performance improvement. Nonetheless, further analyses could employ a wider dataset with more features encoding the different types of missing data, which was not possible in this analysis due to limited computational resources.

Additionally, LASSO regression was an effective model but is not the most appropriate for measures of material hardship and life satisfaction as they are bounded, ordinal measures (Rigobon et al., 2019). Rigobon et al. (2019) addressed this and explored non-linear models, but found that linear models performed best. Nonetheless, they argue that better models for bounded regression should be developed. Further, the higher MSE values on the holdout test set from the validation set may also imply that the models may not generalize as well to unseen data. Overall, it should be noted that the predictability of life outcomes is limited, as no model in the Fragile Families Challenge had strong predictive accuracy (Salganik et al., 2020).

Furthermore, the measures of life satisfaction are constrained, with a narrow scale from 1 to 4. Thus, they provide a limited measure of life satisfaction that may not represent more granular variation for such a subjective measure. Future efforts to predict material hardship could consider using a more granular or multidimensional measure of life satisfaction to capture more detail.

Lastly, while life satisfaction was revealed to be a strong predictor of material hardship, no causality can be assumed. There can be several confounding factors, though there is a longitudinal observation as life satisfaction at Year 9 was a strong predictor for material hardship at Year 15. Nonetheless, further analysis using causal inference techniques would be necessary to establish the direction of the relationship. The importance of life satisfaction could be explained by the assumption that this variable encompasses many other life experiences that affect household outcomes and material hardship. As past material hardship is another notable predictor, it is also possible that prior material hardship could result in lower life satisfaction and vice versa, which could in turn predict future material hardship. These relationships provide an interesting avenue for future research.

6 Conclusion

The findings from this analysis revealed a key insight that subjective well-being measures for mothers or primary caregivers can be important predictors for future material hardship. This provides evidence for the importance of subjective well-being measures, which can capture essential information about households that can inform their future hardship. This supports the numerous movements advancing subjective well-being measurement above economic metrics. Beyond this, the findings support the value of subjective well-being even when economic outcomes are prioritized, as it can support predictions of economic hardship. Moreover, the study showed the value of going beyond black box model performance, focusing on model interpretability to understand predictions as complex as life outcomes.

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7 Appendix

Domain	Question
Food Hardship	(1) In the past twelve months, did you receive free food or meals? (2) In the past twelve months, were you ever hungry, but didn't eat because you couldn't afford enough food?
Housing Hardship	(1) In the past twelve months, did you ever not pay the full amount of rent or mortgage payments? (2) In the past twelve months, were you evicted from your home or apartment for not paying the rent or mortgage? (3) In the past twelve months, did you move in with other people even for a little while because of financial problems? (4) In the past twelve months, did you stay at a shelter, in an abandoned building, an automobile or any other place not meant for regular housing, even for one night?
Medical Hardship	(1) In the past twelve months, was there anyone in your household who needed to see a doctor or go to the hospital but couldn't go because of the cost?
Utility Hardship	(1) In the past twelve months, did you not pay the full amount of gas, oil, or electricity bill? (2) In the past twelve months, was your gas or electric services ever turned off, or the heating oil company did not deliver oil, because there wasn't enough money to pay the bills? (3) In the past twelve months, was your telephone service (mobile or land line) cancelled or disconnected by the telephone company because there wasn't enough money to pay the bill?
Bill-Paying Hardship	(1) In the past twelve months, did you borrow money from friends or family to help pay bills?

Table A.1: Material Hardship Questions

Name	Label	Respondent	Subtopics	Wave
m5g0	G0. How satisfied you are with your life overall	Mother	attitudes/ expectations/ happiness	Year 9
m5f23e	F23E. Did not pay full amount of gas/oil/electricity bill in past 12 months	Mother	material hardship	Year 9
m5f23k	F23K. Telephone service disconnected because wasn't enough money in past 12 months	Mother	material hardship ; home environment	Year 9
m5f23g	F23G. Borrowed money from friends/family to help pay bills in past 12 months	Mother	material hardship ; private transfers	Year 9
m4i23n	In past year, phone service disconnected b/c wasn't enough money?	Mother	material hardship ; home environment	Year 5
m3i23d	In past year, did you not pay full gas/oil/electricity bill?	Mother	material hardship	Year 3
m3i23e	In past year, did you borrow money from friends/family?	Mother	material hardship ; private transfers	Year 3
m5f23a	F23A. Received free food or meals in past 12 months	Mother	material hardship	Year 9
m3i7f	Since child's first birthday: helped by employment office?	Mother	public transfers and social services	Year 3
p4f1f	F1f. There are quite a few things that bother you about your life	Primary Caregiver	parenting abilities	Year 5

Table A.2: Top 10 LASSO Features

Best Parameters	
Random Forest	
max depth	40
max features	sqrt
min samples leaf	1
min samples split	8
n estimators	175
LASSO	
alpha	0.012

Table A.3: Best Parameters For Material Hardship Models

Name	**Label**	**Respondent**	**Subtopics**	**Wave**
m5g0	G0. How satisfied you are with your life overall	Mother	attitudes/expectations/hap	Year 9
m5f23g	F23G. Borrowed money from friends/family to help pay bills in past 12 months	Mother	material hardship ; private transfers	Year 9
cm4hhinc	Constructed - Household income (with imputed values)	Mother	household income/poverty	Year 9
m5f23e	F23E. Did not pay full amount of gas/oil/electricity bill in past 12 months	Mother	material hardship	Year 9
m5f23k	F23K. Telephone service disconnected because wasn't enough money in past 12 mont	Mother	material hardship ; home environment	Year 5
m4i23n	In past year, phone service disconnected b/c wasn't enough money?	Mother	material hardship ; home environment	Year 3
m4i23d	In past year, did not pay full amt rent/mortgage payments b/c wasn't enough	Mother	material hardship	Year 3
m5f23a	F23A. Received free food or meals in past 12 months	Mother	material hardship	Year 9
m4i23h	In past year, borrow money from friends or family to help pay bills?	Mother	material hardship ; private transfers	Year 3

Name	Label	Respondent	Subtopics	Wave
p4f1j	F1j. You are less interested in people than you used to be	Primary Caregiver	parenting abilities	Year 5

Table A.4: Top 10 Random Forest Features