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Research Paper

Factors Influencing Domestic Violence Among Child Laborers

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ABSTRACT: *Child labor remains a significant global issue, particularly acute in developing countries like Myanmar. This study examines the factors influencing child labor among children aged 5-17 Years in Nay Pyi Taw City. Child labor in Myanmar is primarily driven by poverty, unemployment, and traditional norms. The research utilizes logistic regression, random forests, and lasso regression models to analyze data on child laborers. Findings indicate that family income, employment status of the parents, and regional development significantly influence child labor. The study underscores the need for comprehensive policies, strict enforcement of child labor laws, and socio-economic improvements to combat child labor effectively. Collaborative efforts from government, NGOs, and international organizations are essential for education, healthcare, and better opportunities for affected children. This research contributes to understanding the complex socio-economic dynamics of child labor and offers insights for developing effective interventions and policies.*
KEYWORDS*: Child Labor, Binary Logistic Regression, Random Forest, Lasso Regression, Poverty*

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I. INTRODUCTION

Zaw, Kaung Myat. (2019) found that poverty was the main cause of child labor in Myanmar, a developing country. This study highlighted that the children engaged in this labor were found to be working in restaurants, teashops, and food centers to support their economically disadvantaged families. The survey revealed that 97.5 percent of employers shoulder the responsibility for the basic needs of these child laborers, provide skill enhancement job insurance, and strive to create a suitable working environment, but these youngsters are caught in a repetitive pattern of need, which not only deprives them of important chances for education and personal growth but also exposes them to dangerous and exploitative labor circumstances. However, the weight of work eclipses their youthful dreams and goals, resulting in damaged physical and mental health. To effectively tackle this deeply rooted problem, it is crucial to prioritize joint endeavors. To address the issue of child labor, it is necessary to implement thorough policies and strict enforcement of laws against child labor. Additionally, committing to tackling the underlying causes of poverty and unemployment is crucial, the main factors pushing children into the labor market. Additionally, combatting child labor demands a holistic approach to recognizing the intricate socioeconomic factors involved. By breaking this cycle and providing avenues for education and upward mobility, we pave the way for a generation of empowered individuals who can shape a brighter future for themselves, their families, and their nations. Based on prior research conducted by the International Labor Organization (ILO), it is estimated that approximately 265 million children (constituting 17% of the global child population) are engaged in child labor worldwide. Within Myanmar, the International Labor Organization identifies around 1.1 million children aged between 5 and 17 years who are involved in labor, including those subjected to child labor.

Myanmar is a developing nation, displaying a literacy rate of approximately 89.07% in the year 2019, as per preceding research findings. Nevertheless, the issue of child labor remains pervasive across numerous regions, driven by factors such as insufficient income levels, socio-economic challenges, and entrenched traditional norms. Despite the government's efforts to address this concern through policy initiatives, there persists a prevalence of severe forms of child labor. Occupations like cleaning, washing, cooking, waiting, and even begging continue to ensnare young lives in exploitative circumstances. Over the period spanning from 2000 to 2020, there has been a discernible reduction in the incidence of child labor, with the proportion dwindling from 16% to 9.6%. The imperative for stringent enforcement of laws, comprehensive policy implementations, and impactful programs remains unequivocal. The task at hand necessitates an unwavering commitment to eradicating all forms of child labor, ensuring that the potential and dignity of every child are protected and nurtured. Thus, this study aims to investigate the influence factors on child labor aged between 5-17 years olds in Nay Pyi Taw City, Myanmar.

In 2019, a significant milestone was achieved in Myanmar as the government introduced a comprehensive law focused on safeguarding Child Rights. To effectively ensure the enforcement of this legislation, the government took a crucial step by establishing the National Committee for the Rights of the Child. This committee was tasked with the critical responsibility of formulating and implementing a range of policies, guidelines, and measures to uphold children's rights across the nation. While the government has taken steps to provide information and data related to child labor, it is evident that further action is required. The dissemination of information is an important initial step, but the true impact lies in implementing comprehensive programs that create tangible change on the ground. Collaborative efforts involving government organizations, NGOs, communities, and international organizations are essential to design and execute initiatives that directly address child labor, providing affected children access to education, proper healthcare, and opportunities for a brighter future. In essence, the journey toward eradicating child labor in Myanmar's conflict areas is an ongoing one that demands unwavering dedication and multi-faceted strategies. By consistently bridging the gap between policy formulation and effective implementation, the nation can move closer to ensuring that every child's rights are respected and upheld, regardless of the challenges they may face in their environment.

1.1 NEXUS BETWEEN DEMOGRAPHIC VARIABLES AND CHILD LABOR

According to global child labor estimates, 48% of child laborers were aged 5-11 years, 28% were aged 12-14 years, and 24% fell within the 15-17 age range. Moreover, when considering gender, 58% of total child labor consisted of males, while females accounted for 42% worldwide (ILO, 2017). The agricultural sector held 70.9% of child labor, industry constituted 11.9%, and services encompassed 17.2%. Despite the International Labor Organization's (ILO) efforts to eliminate child labor by 2025, approximately 152 million children were still engaged in child labor, with almost half of them enduring its worst forms (ILO, 2017).

The primary causes of child labor in Africa depended on the presence or absence of their parents. Moreover, the poorer the family, the more likely child labor was, and if the family income increased, the rate of child labor dropped (Andvig, 2001). Thus, there was a positive correlation between poverty and the rate of child labor participation. By comparing to other regions, Sub-Saharan Africa had the greatest percentage of child labor, it was about twice that of Asian countries. Children who lived with their fathers were more likely to attend school and less likely to work. Child labor participation rates might be high because of the high fertility rate in Africa.

In 2010, employment among children aged 10 to 15 years old was 7.74% in China (Tang et al., 2018). On average, they worked for 6.75 hours per day and studied for 6.42 hours less than other students. It was more probable for children to labor in rural areas. The widespread child labor in China varied significantly not only by region but also by level of development. Liang and Chen (2007) studied school enrollment figures for migrant children living in Guangdong cities in 1995 by using multivariate analysis. This study found that the rate of school enrollment for temporary migrants was notably lower in comparison to that of local children. The disparities in access to education emphasized the challenging obstacles that migrant communities had to overcome in providing quality education for their children. This necessitated a thorough analysis of the underlying factors and the development of focused strategies to close the educational gap.

Shilongo (2021) identified the factors contributing to child labor and analyzed child labor patterns in Namibia using the data from the last five national labor force surveys. This study found that geographical areas, regions, sex, age groups, literacy status, and level of education of children were statistically significant on child labor at a 0.05 significance level. The predictive performance of the traditional logit model was investigated in contrast to artificial neural networks by using child labor data from Peru (Libaque-Saenz et al., 2017). The study's findings, presented with compelling evidence, showcased that neural networks had a notable capacity to produce predictions of heightened accuracy compared to the logit model. The research findings illuminated various noteworthy factors that predict child labor occurrence. Moreover, the geographic indicators, income levels, gender, family composition, and educational levels emerged as robust factors that distinctly influenced the occurrence of child labor.

1.2 NEXUS BETWEEN SOCIO-ECONOMIC VARIABLES AND CHILD LABOR

Child labor was influenced by specific factors that issued from differences in their socio-economic backgrounds in Pakistan (Khan et al., 2010). Moreover, the education level of the household head had a positive impact on child schooling. Its influence was stronger for urban households. In urban areas, the employment status of the household head positively affected child schooling, whereas in rural areas, it had a negative impact. In urban areas, a mother's employment benefited child schooling and mitigated child labor. However, in rural areas, it replaced child schooling and had a positive association with child labor. Using the data from rural Pakistan, the correlation between temporary economic migration and investments made in child education (Mansuri, 2006). Children residing in migrant households might encounter elevated emotional strain, as the disruption in familial routines and separation from parents led to feelings of insecurity and uncertainty. Additionally, the experience of reduced adult oversight due to parental absence could expose them to unique challenges and decisions that they might not be fully equipped to handle on their own. Children who were not subjected to the constraints of child labor experienced the opportunity to completely actualize their entitlements to education, leisure, healthy development, poverty eradication, and human rights (ILO, 2017).

Economic distress forced children to give up their education, and the jobs were underpaid and hazardous (ILO, 2015). Additionally, this study found that the literacy rate among females was significantly lower than males, underscoring a gender gap in education access in Myanmar. Financial resources are insufficient to meet even the necessities; children are unfortunately left with limited options. The pressing need for additional income to sustain the family's livelihood becomes a compelling force that drives these young individuals into the workforce. Performance of indicators to evaluate urban models safeguarding child labor rights in the urban industrial zones of Yangon, Myanmar (Pa Pa Soe, 2017). This study mentioned that the root causes of child labor were intricate, with poverty being a driving factor due to families' financial constraints. Poor education deepened the problem, as children lack the skills to escape labor. Child labor arose due to family indebtedness, driven by the need to repay loans. Limited awareness of labor laws perpetuated the issue, and families were unaware of protections. Children living in rural areas moved to urban areas like Yangon after disasters due to low family income (Pa Pa Soe, 2017). Solangi et al. (2022) discovered that age, maternal education, parental marital status, and family member count had notable impacts on child labor. However, gender, paternal occupation, and parental encouragement lacked statistical significance in this study.

Child labor occurs within households and is managed by the children's relatives, and poverty is the leading cause of child labor, particularly prominent in Africa, the most economically deprived continent (Blunch et al., 2001). Moreover, within African regions, those characterized by lower economic status showed higher instances of child labor. Additionally, the study identified that an increase in the number of adults or family income reduced the necessity for children's labor. The economic activities of children and their learning achievement were analyzed by using test scores in Ghana (Heady, 2000). Concurrently, attending school and engaging in labor was not feasible for child laborers. Thus, in that complex scenario, the child could have acquired informal education through practical knowledge from their work experiences and daily interactions. Although child laborers might have received vocational training, technologies, and experience from their workshops, the results indicated that the working of children was largely negatively affected by their education. Child labor was influenced not only by the extent of poverty but also by supplementary elements like the expenses related to schooling and transportation, which compounded the problem's pervasiveness (Pickard et al., 2003). These intertwined challenges collectively underscored the multifaceted barriers that children from disadvantaged backgrounds face, reinforcing the need for holistic strategies to combat and alleviate the scourge of child labor.

Family incomes experienced an upward trajectory in developing countries, and a corresponding decline in child labor instances was observed, illustrating a positive correlation between economic improvements and the reduction of exploitative labor practices involving children (Deardorff and Stern, 2011). Despite a decline in the number of working children in Asia and Latin America, the specter of child labor continued to cast its darkest shadow over Africa, primarily driven by a confluence of factors such as economic recession, the ravages of war, pervasive famine, and the unrelenting grip of the HIV epidemic. Ethiopia was one of the countries with the highest levels of child labor, and its primary school enrolment was the lowest in the world.

1.3 NEXUS BETWEEN DOMESTIC VIOLENCE AND CHILD LABOR

Morei (2014) analyzed domestic violence legislation in South Africa, assessing the extent to which the government had upheld its constitutional duty to safeguard the rights of women and children. This study found that the average age of girls who had experienced sexual abuse was eleven years old. In addition, among reported crimes, sexual offenses accounted for more than half (52%) of those directed at children, whereas they constituted only 19% of the crimes against adult women. Thus, it was imperative to ensure the protection of children from maltreatment, neglect, abuse, and degradation. This constitutional directive, which prioritized a child's best interests above all else, extends to matters involving domestic violence against children. Pa Pa Soe (2017) revealed that children encountered numerous challenges due to exploitation, violence, and workplace hardships. Home-based domestic child labor also confronted barriers like inadequate legal safeguards, monitoring, education, and awareness programs, creating an ongoing cycle of vulnerability and exploitation.

The eradication of hazardous and the worst forms of child labor was targeted through a dedicated child labor program, while efforts to eliminate non-hazardous child labor that was deemed unacceptable were largely integrated into the regular initiatives of programs, international organizations, and national ministries (Anker, 2000). One of the main factors affecting working for children was poverty (Suryahadi et al., 2005). Globally, girls were less likely than boys to work as children by comparing to boys (ILO, 2017). In addition, there was a strong relationship between situations of conflict, disaster, and child labor. Furthermore, most of the child labor occurred within the family. It was not only related to the gender of the head of the household and the occurrence of child labor but also related to the education level of the household head. The occurrence of child labor was higher among female-headed households than the male-headed household (ILO, 2015). In addition, with higher levels of education of household heads, child labor quickly diminished.

Mudzongo (2020) discovered that the elements contributed to the escalation of children's working hours in Malawi and Tanzania. The mean working hours for Malawi was 38.35 hours, and for Tanzania was 40.04 hours. This study found a statistically significant correlation between age and the number of hours worked by child laborers. The correlation coefficients for Malawi and Tanzania were 0.148 and 0.220, respectively; when children grew older, they tended to work more hours.Labor conditions, the weekly hours committed to work, and the presence of morning work schedules had a detrimental impact on the academic performance of child laborers (Holgado et al., 2014). Individuals who had encountered childhood trauma exhibited a propensity for substance abuse, minimizing the adverse effects of their earlier ordeals, especially when inflicted by their parents (Downey and Crummy, 2022). They constructed a false self-image instead of isolating themselves from society. Early exposure to trauma could contribute to lowered self-esteem, potentially resulting in the development of depression and anxiety triggered by feelings of inadequacy.Over 35% of the participants revealed they had experienced at least one adverse childhood event. Among young individuals with a history of trauma, more than 50% reported multiple instances of traumatic exposure (Redican et al., 2022).

1.4 NEXUS BETWEEN CULTURE, TRADITIONAL NORMS, AND CHILD LABOR

ILO (2017) found that boys had a greater risk of child labor than girls, as evidenced by numerous global studies and reports highlighting their higher involvement in sectors such as agriculture, manufacturing, and construction. This discrepancy could be attributed to a complex interplay of cultural norms, economic conditions, and limited access to education. Moreover, girls were much more likely than boys to shoulder responsibility for household chores, a form of work not considered in the child labor estimates. This inequitable distribution of domestic tasks not only reinforced traditional gender roles and biases from a young age but also perpetuated a cycle that could impact girls' educational opportunities, personal development, and future career aspirations.

The dissemination of information is an important initial step, but the true impact lies in implementing comprehensive programs that create tangible change on the ground. Collaborative efforts involving government organizations, NGOs, communities, and international organizations are essential to design and execute initiatives that directly address child labor, providing affected children access to education, proper healthcare, and opportunities for a brighter future. In essence, the journey toward eradicating child labor in Myanmar's conflict areas is an ongoing one that demands unwavering dedication and multi-faceted strategies. By consistently bridging the gap between policy formulation and effective implementation, the nation can move closer to ensuring that every child's rights are respected and upheld, regardless of the challenges they may face in their environment.

II. SIGNIFICANCE OF THE STUDY

This study focused on the child laborers who live in Nay Pyi Taw City. This study used logistic regression, random forests, and lasso regression models by comparing the results of these three models, which are better and fit the data. UNICEF (2007) estimated that approximately 317 million children aged between 5 and 17 were employed globally. 218 million of these children were identified as child laborers, of which 126 million worked in dangerous occupations such as coal mining and military combat (International Labor Organization, 2006). Thus, child labor is an important problem around the world. Violation of children's rights and domestic violence in child labor play a key role in developing countries. A huge of violence against children is committed not only by a stranger but also by a family member due to poverty, insufficient family income, low education level, and less development in the country. Children cannot escape from the poverty trap. They are forced to be child laborers, especially the developing countries like Myanmar. Most children from rural areas migrate to urban areas for work/ better income. This study investigates the children working in Nay Pyi Taw City aged 5-17 years old for both males and females.

III. OBJECTIVES OF THE STUDY

This study focuses on examining what factors have the most influence on domestic violence among child laborers aged 5- 17 years who live in Nay Pyi Taw, Myanmar. The other objectives are

1. To explore the influence factors on domestic violence of child labor.
2. To investigate the living conditions and working status of child labor.
3. To monitor the usage and powerful of the random forest model, logistic regression model, and lasso regression model.

IV. CONCEPTUAL FRAMEWORK OF THE STUDY

To ascertain the research objectives, the analysis encompasses demographic variables, socio-economic factors, and traditional norms variables. This study not only investigates the influencing factors on domestic violence within child labor but also delves into the application of supervised learning methods. Additionally, this research endeavors to elucidate the socio-economic conditions surrounding child labor. Moreover, the findings from this paper are poised to contribute to the development of more effective policies and lay the groundwork for further studies on child labor in the region. The conceptual framework was developed to specify the meaning of the concepts that can be used on the variables to be studied. Figure 1 shows the relationship between the study variables. Child labor may be related to individual factors, household factors, and traditional norms factors.

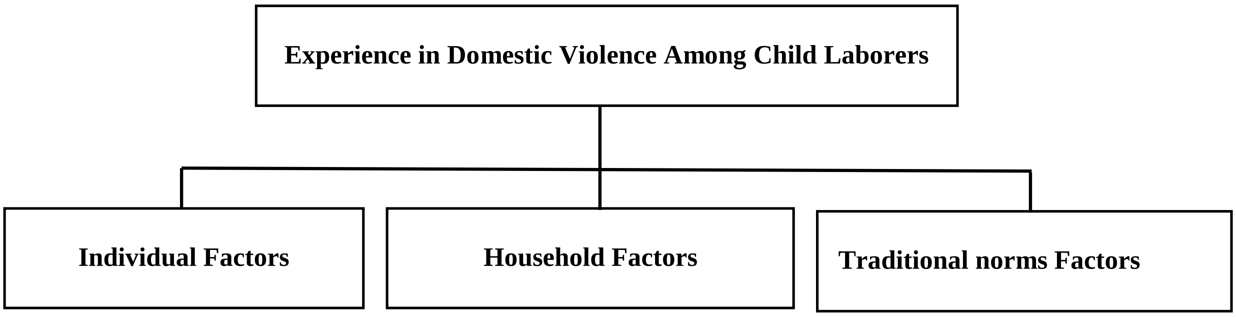

Figure 1 Conceptual Framework of Child Labor

Source: Author Design

V. METHOD OF THE STUDY

This study analyzes the data using binary logistic regression, random forest, and logistic lasso regression models. the random forests address overfitting by utilizing subsets of predictor variables in modeling. Comprising an ensemble of decision trees created through sampling with replacement, the random forest classifier explores all possible feature combinations and sample repetitions (R et al., 2020). With each new training set, decision trees progressively deepen, incorporating diverse feature combinations, providing an advantage over traditional decision tree methods. The random forest model allows for deriving variable importance measures, and its method of splitting is subjected to randomization (Louppe, 2014). Logistic regression, a widely used tool, is essential in statistics and machine learning for categorizing binary output based on input variables, standing out for its practicality and frequent application in discrete data analysis (El Morr et al., 2022). Lasso regression method facilitates the incorporation of numerous covariates by penalizing the absolute values of regression coefficients, effectively regulating their influence (A. McEligot et al., 2020).

5.1 LOGISTIC REGRESSION

Socio-economic variables were predominantly categorical rather than measured on an interval scale. In many research studies, the emphasis was placed on models where the dependent variable was likewise categorical (Elliot, 2008). There are some assumptions in the logistic regression model: the dependent variable is the binary outcome, and the log odds of the dependent variable being in a particular category is a linear combination of the independent variables (Harrell, 2015). In other words, the relationship between the independent variables and the log odds is linear (Sreejesh et al., 2014). It assumes that the observations are independent of each other and that there is little or no multi-collinearity among the independent variables. The importance is that a large enough sample size is assumed to ensure stable parameter estimates and reliable statistical inference.

The binary logistic regression model is

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots . + \beta_p X_p$$

$where;\ p$ is the probability of the dependent variable being 1.

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots . + \beta_p X_p)}}$$

$X_1, X_2, \dots, X_p$ are the predictor variables.

β_0 is the intercept term.

$\beta_1, \beta_2, \dots \dots, \beta_p$ are coefficients of the predictor variables.

5.2 RANDOM FOREST MODEL

Random forests are ensembles of decision trees. They improve predictive accuracy by combining the results of multiple decision trees. The random forest classification model is an ensemble learning method that combines multiple decision trees to make predictions (Lsta et al., 2012). In the random forest model, randomly select a subset of the data (with replacement) to create multiple bootstrap samples. These samples are used to build individual decision trees. The random forest model formula is a bit more complex than a single decision tree.

$$H(X) = Mode\ [H_1(X), H_2(X), \ldots\ldots, H_N(X)]$$

where; $H_i(X)$ is the output of the i^{th} decision tree for input X. The "Mode" function calculates the most common prediction (class) among all the decision trees in the forest, effectively determining the final predicted class.

5.3 LOGISTIC LASSO REGRESSION OR L1-REGULARIZED LOGISTIC REGRESSION

The L1 regularization term encourages sparsity in the model by penalizing the absolute values of the coefficients, which helps in feature selection and can make some coefficients exactly zero (Vidaurre et al., 2013). The optimization algorithm used to estimate the coefficients in logistic lasso regression seeks to minimize the following loss function:

$$Loss = -\sum_{i=1}^{n}[y_i * \log(p_i) + (1 - y_i) * \log(1 - p_i)] + \lambda \sum_{j=1}^{q}|\beta_j|$$

Where, y_i is the actual binary outcome for the i^{th} observation.
p_i is the predicted probability of the i^{th} observation being 1.
n is the number of observations.
q is the number of predictor variables.
λ is the regularization parameter that controls the strength of the L_1 penalty.

5.4 SAMPLE AND SAMPLING DESIGN

The study used a 259-sample size. The primary survey data was gathered from child laborers aged between 5 and 17 years, actively engaged in work within Nay Pyi Taw City in Myanmar. In Nay Pyi Taw, there are eight townships such as Pobbathiri township, Ottarathiri Township, Zabuthiri Township, Zeyarthiri Township, Dekhinathiri Township, Tatkone, Pyinmana, and Lewe Township. The research methodology involved a systematic approach, beginning with the design of a meticulously structured questionnaire dedicated to the exploration of various facets of child labor. This questionnaire underwent refinement through a comprehensive focus group discussion, ensuring its relevance and effectiveness. The subsequent phase involved the actual implementation of the survey, utilizing face-to-face interviews to interact directly with the respondents and gather valuable insights. Employing a convenience sampling method facilitated the collection of data from 259 respondents. The face-to-face interviews provided a robust foundation for data acquisition and fostered a more in-depth understanding of the unique circumstances and challenges faced by child laborers in Nay Pyi Taw City.

5.5 DATA AND VARIABLES

In this study, the focal point of analysis centers around the experience of domestic violence, designated as the dependent variable, denoted by binary outcomes (Yes=1, No=0). In exploring the complex dynamics associated with domestic violence, a comprehensive set of explanatory variables has been employed across three distinct models: binary logistic regression, lasso regression, and random forests.

The array of explanatory variables encompasses individual, household, and traditional norms and custom variables, forming a multifaceted approach to understanding the factors influencing domestic violence. In particular, the independent variables encapsulate demographic characteristics, shedding light on the intricate interplay of individual factors such as age, gender, and education, as well as economic characteristics that delve into aspects of both individual and household dynamics. Furthermore, the inclusion of traditional norms and customs factors underscores the broader socio-cultural context that may contribute to the occurrence of domestic violence. Both R-Studio and SPSS will be used to analyze data.

VI. RESULTS

6.1 SUMMARY STATISTICS

Table 1 shows the important information on child labor in this study. Although the other studies indicated that child labor is significantly more prevalent among girls than boys, this study finds that higher number of female child laborers than males because 52.51% is female child labor and 47.49% is male labor. This reason is that Myanmar has a large number of females population. Rural area has 75.3% of child labor and urban has 64%. Thus, rural areas have more child labor than urban areas due to less development. The most occurrence of number of siblings is four to ten, and 46.3% of this study. The second largest frequency is one to three and 45.9%. Thus, this study finds that the more siblings there are, the more chance there is to be child labor because the large family size and low income make the children laborer. The minimum child labor age is seven years old, with the lowest percentage of 0.4%, and the maximum is seventeen years old, at 42.5%. As an age group, there are 16.2% in seven to thirteen years old, 18.9% in fourteen to fifteen years old, and 64.9% in sixteen to seventeen years old. As a result, it found that the sixteen to seventeen age group has the highest frequency of child labor age in Nay Pyi Taw City. The middle school level is the most chance to drop out and work for a living. Another finding is that the main reason for working is due to the low income of the family, which is about (66. 2%) of this study. The first child or the eldest child has the biggest chance to be a child laborer. About 83.4 % are the eldest child in this study. 93.1% are single, and 6.9% are married.

Table 1 Summary Statistics for Studied Variables of Child Labor

Sr	Variable Name	Category	Frequency	Percent
1	Sex	Male	123	47.49%
		Female	136	52.51%
2	Region	Rural	195	75.3%
		Urban	64	24.7%
3	Age Group	Seven to thirteen years old	42	16.2%
		Fourteen to Fifteen years old	49	18.9%
		Sixteen to Seventeen-year-old	168	64.9%
4	Education Level	Primary School	47	18.1%
		Middle School	105	40.5%
		High School	90	34.7%
		Undergraduate	10	3.9%
		Read and Write Only	7	2.7%
5	Family income	Between 80000 and 200000	73	28.2%
		Between 200001 and 300000	131	50.6%
		300001 and above	55	21.2%
6	Number of Siblings	No Sibling	20	7.7%
		One to Three	119	45.9%
		Four to Ten	120	46.3%
7	Marital status of the parents	Divorced	14	5.4%
		Passed away / Died	50	19.3%
		Staying together	195	75.3%
8	Marital Status of the respondents	Single	241	93.1%
		Married	18	6.9%
9	If you are married, do you have a child?	Yes	5	1.9%
		No	254	98.1%
10	Does your father have a job?	Yes	168	64.9%
		No	91	35.1%
11	Does your mother have a job?	Yes	158	61%
		No	101	39%
12	Student of Siblings	Yes	136	52.5%
		No	123	47.5%
13	Working Hour	Five Hours to Nine Hours for a day	48	18.5%
		Ten Hours to Twelve Hours for a day	211	81.5%
14	Family Size	One to four members	89	34.4%
		Five to Six members	98	37.8%
		Seven to Twelve	72	27.8%
15	Reasons for Work	Due to the low income of the family	171	66%
		Due to dislike to attend the school	88	34%
16	Behavior of Boss	A little bad (or) Not fair	65	25.1%
		Fair	193	74.5%
		Good	1	0.4%
17	Do you have experience in Domestic Violence	Yes	79	30.5%
		No	180	69.5%
18	Kinds of Domestic Violence that the respondent experienced	Physical Violence	10	12.66%
		Mental Violence	67	84.81%
		Sexual Violence	2	2.53%
17	Your Position among siblings in your family	First Child among them	216	83.4%
		Second Child among them	25	9.7%
		The last Child among them	16	6.2%
		Others	2	0.8%

Source: Survey data (2022)

6.2 BINARY LOGISTIC REGRESSION MODEL

By using the binary logistic regression model, experience in domestic violence is the dependent variable, and "identification of townships, region (rural, urban), sex, age of the respondent, number of siblings, your position, marital status, respondent education level, family income, family size, do respondent's father have a job, respondent income, respondent's income supports the family's expenditure" are the explanatory variables. In this study, binary logistic regression uses different explanatory variables because logistic regression cannot give a good result if more explanatory variables are added.

The binary logistic regression model shows that the omnibus test of the model coefficient's P-value is 0.000. Thus, there is statistical significance between the domestic violence and explanatory variables as well and the model is a good fit. The explanation percentage of the model is about 84.6%. The Nagelkerke R square is 57.6%. Thus, 57.6% of the variance can be explained by the predictor variables. The respondent income (P-value=0.000), identification of townships (P-value=0.003), region (rural, urban) (P-value=0.025), sex (male, female) (P-value=0.023), the position of the respondents in their households (P-value=0.049), do their fathers have a job (P-value=0.005), income support the family expenditure (P-value=0.020) are statistically significance at 5% level. The respondent's income, identification of townships, gender, respondents' position in their households, employment status of their fathers, and income support the family expenditure influence on domestic violence in this study.

Table 2 Brief Results of Binary Logistic Regression

Omnibus Tests of Model Coefficients		**Nagelkerke R Square**	**Hosmer and Lemeshow Test**	**Overall Percentage**
Chi-square	135.511	0.576	0.089	84.6%
Significance	0.000 ***			

Source: Survey data (2022)

6.3 RANDOM FOREST CLASSIFICATION MODEL

In this study, the random forest model is used for classification. Using the random forest model, the dependent variable is experience in domestic violence, and individual variables, household variables, and traditional norm variables are independent variables. The results of the random forest model from the R Studio are shown in the following figures.

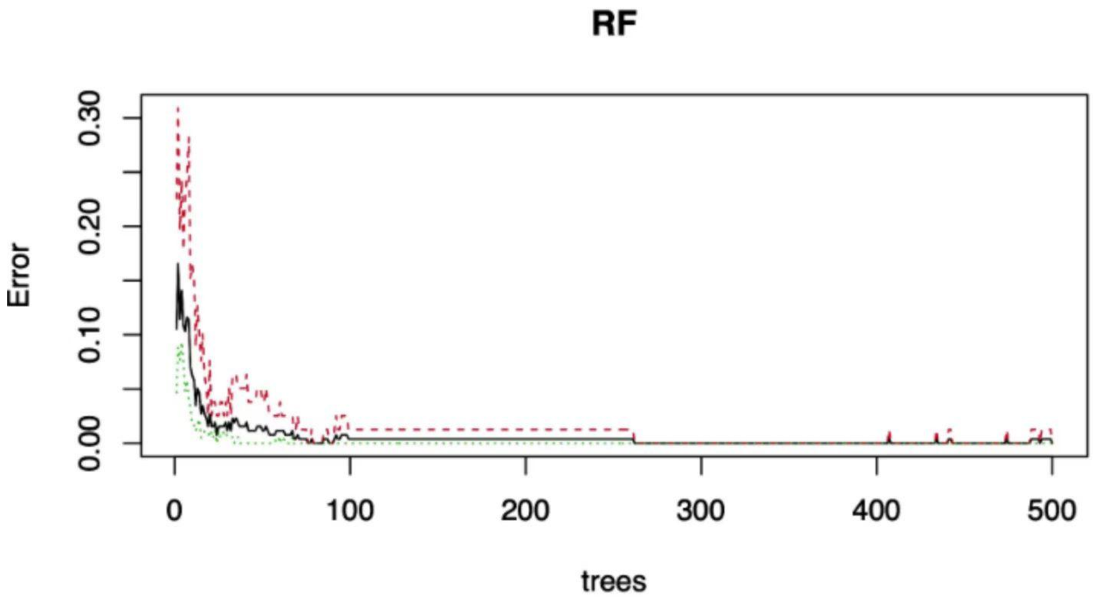

Figure 2 Number of Trees and Their Corresponding Errors
Source: Survey data (2022)

Figure (2) shows the error of the random forest model and their corresponding trees. The result finds that the error is 0.00 when the trees are about 100. The greater the trees, the error will be zero.

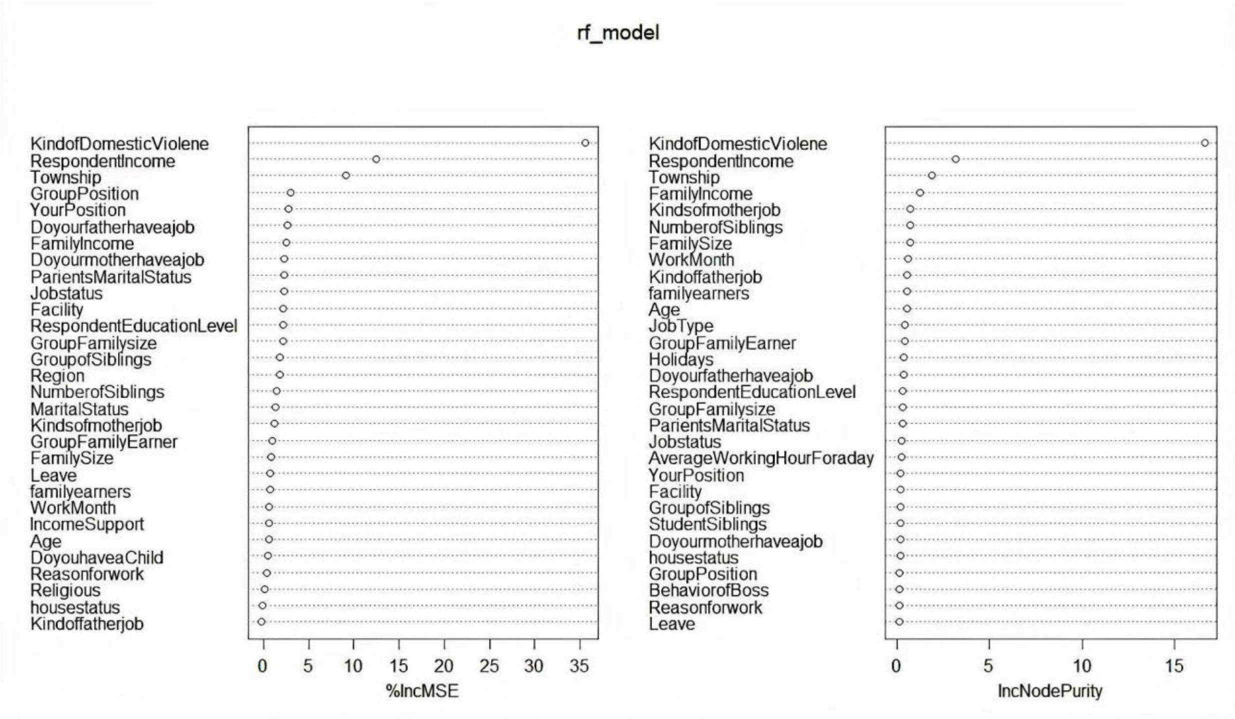

Figure 3 Importance Variables Description of Child Labor by using Random Forest
Source: Survey data (2022)

Figure (3) describes the values of "% IncMSE" and "IncNodePurity" of the studying variables by using the random forest model. They are commonly used metrics to understand the importance of features (variables) in predicting the target variable in a random forest model. % IncMSE can be used to identify which features are the most influential in the random forest model. This figure describes that kinds of domestic violence, respondent income, and township (region of the respondents) are the most influential variables in child labor. In brief, the random forest model shows (the OOB) estimate of the error rate is 0%. The number of trees is 500. Number of variables tried at each split is 5. Table (3) shows the brief results of the random forest model.

Table 3 Brief Results of the Random Forest Model in Child Labor

OOB estimate of error rate	0%
Number of trees	500
No. of variables tried at each split	5

Source: Survey data (2022)

6.4 LOGISTIC LASSO REGRESSION MODEL

The goal of the logistic lasso regression model is to find the values of the coefficients. β that minimize this loss function, and the L_1regularization term encourages some coefficients to be exactly zero, effectively selecting a subset of the most important features for the classification task (A. J. McEligot et al., 2020). The strength of regularization λ can be adjusted to control the level of sparsity and the number of selected features.

In this study, the dependent variable is "experience in domestic violence," and the independent variables are age, the position of the respondents in their families, family income, number of siblings, education level of the respondents, parents' marital status, family size, family earners, respondent income, respondent's income supports for the family expenditure. The logistic lasso regression assumes that the relationship between the independent variables and the log odds is linear and that the observations are independent of each other. There is little or no multi-collinearity among the independent variables, and it needs a large enough sample size. The relationship between the independent variables and the log odds should be approximately linear. In this study, logistic lasso regression mentions that different lambdas, the coefficients, and the best lambda value is 0.01258355. The importance variable of the lasso regression model is shown in the following table.

Table 4 Importance Variable Description of Child Labor by Using Lasso Regression Model

Intercept	RI (Respondents' Income)
-2.206398 e-01	-5.639864e-06

Source: R-Studio Output

Table 4 shows that respondent's income is the important variable in the experience of domestic violence among child labor. There is a negative relationship between the income of the respondents and their experience with domestic violence.

VII. DISCUSSIONS

Although the previous studies indicated that child labor is significantly more prevalent among boys than girls (ILO, 2017), this study finds that a higher number of female child laborers than males. This is because Myanmar has a large number of females. A rural area has a greater number of child laborers than an urban area due to less development. It has been observed that the predominant occurrence is mental violence, commonly identified as emotional violence. This form of violence encompasses a wide range of psychological and emotional actions or behaviors that have surfaced as a significant focal point within the context of this research.

For the comparison of models, binary logistic regression is a good model for the categorical data analysis, and the coefficients can represent the change in the log odds of the event happening for a one-unit change in the corresponding predictor variable, assuming all other variables are held constant (Elliot, 2008). In other words, these coefficients tell how each predictor variable influences the likelihood of the binary outcome. In this study, income support and experience in domestic violence are negatively correlated. In a binary logistic regression model, the log-odds ratio plays a central role in quantifying the relationship between the independent variables and the probability of the event occurring. The logistic regression model uses the log-odds ratio, also known as the logit function, to model the linear relationship between the independent variables and the log-odds of the dependent variable being in a particular category.

Logistic regression was employed to examine how social support and problem-solving ability influence a predictive model (Jurafsky and Martin, 2021). This model determines event probabilities by fitting data to a logistic curve through several predictable variables, which can be either qualitative or quantitative (Ahmed et al. Helal, 2020). Moreover, logistic regression assumes that there are no significant outliers in the data that can unduly influence the parameter estimates and model fit. If the assumptions are violated, logistic regression can lead to poor model performance. Thus, logistic regression serves as a tool for assessing moral factors and quantifying the impact of independent variables on a binary dependent variable. Logistic regression can accommodate both qualitative independent variables and interactions between these factors. It also circumvents many of the constraints inherent in least-squares linear regression (Ahmed El Sayed and Abu Bakr Helal, 2020).

The random forest model does not need linearity assumptions (Schonlau and Zou, 2020). It can handle more easily than the logistic regression model when the number of features is larger than the sample size (observations). It works well in this situation because not all predictor variables are used at once (R et al., 2020). It can not only improve the accuracy for regression/ classification of child labor but also conquer the over-fitting problem. In this model, encoding each category with a numerical value will allow the model to perform with the categorical features. It performs well if the values of the numerical features of the test data are within or close to the range of training data (Louppe, 2014). However, it fails to classify correctly if the test data is far outside the training data. The key benefits of the random forest are decreased overfitting risks and shorter training times. It also provides an exceptionally high level of precision. When used to estimate missing data, the random forest operates well in big databases and generates extremely accurate predictions. This model is good for many independent variables because it can produce good predictions and handle large datasets efficiently.

The random forest model does not rely on specific assumptions but assumes that the individual observations are drawn independently and with replacement from the dataset. Its assumptions are related to the nature of decision trees and the bootstrapping and aggregation process used in the ensemble method. It is not sensitive to the scale of the features because it works by splitting the data based on individual features in each tree. It is designed to be robust to overfitting. Moreover, it does not assume linear relationships between the features and the target variable, making it suitable for modeling both linear and nonlinear relationships. Apart from these, it can measure feature importance based on how much each feature contributes to the model's accuracy.

Lasso regression adds a regularization term to the ordinary least squares (OLS) objective function, which encourages sparsity in the model by penalizing the absolute values of the regression coefficients (Ranstam and Cook, 2018). This regularization helps in feature selection and can lead to more interpretable and stable models. Thus, lasso regression can get more precise feature results than the other models (logistic regression and random forest model). In this study, the respondent's income is the most important feature of domestic violence in child labor. The reason is that the L1 regularization term in the objective function encourages the coefficients of less important features to shrink toward zero (Tibshirani, 1996). Thus, the key assumption specific to logistic Lasso regression is using L1 regularization, which encourages sparsity in the model.

In this research, three models use the same dependent variable: experience in domestic violence. However, the binary logistic regression model used a smaller number of explanatory variables because it can give a biased result when more explanatory variables are considered for the analysis. However, the random forest model can give better results when we consider more explanatory variables because random forest makes averaging, and the individual observations are drawn independently and with replacement from the dataset. The lasso regression tries to make some coefficients exactly zero, effectively selecting a subset of the most important features for the classification task. In short, both logistic regression and lasso regression discover that the respondent's income is the most influential variable on child labor, and it is also the most significant value among all predictor variables. The random forest model finds that kinds of violence, respondent's income, and township are influence variables on child labor. However, random forests may perform poorly on datasets with high noise, outliers, or irrelevant features.

In brief, adopting three different models provides a robust analytical framework, each offering unique strengths in capturing and interpreting the underlying patterns within the dataset. Binary logistic regression enables a probabilistic assessment of the likelihood of domestic violence, while lasso regression introduces a regularization technique that aids in feature selection and model simplicity. Utilizing the random forests model, with its ensemble of decision trees, ensures a comprehensive exploration of the intricate relationships among the variables, offering insights into the relative importance of each feature. By integrating these models and variables, this study aims to unravel domestic violence's nuanced complexities, providing a holistic understanding of the contributing factors and paving the way for informed interventions and policy recommendations.

VIII. CONCLUSION

This study makes a substantial contribution to enhancing the living conditions of child laborers and improving their working environment within this region. It explores the reasons for working, working hours, salaries, family income, demographics, socio-economic conditions, and working status. This research also reveals the influence of Myanmar's traditional norms on child labor. This research finds that the position of their siblings has statistical significance on child labor. The reason is that Myanmar has the traditional norm that the eldest brother or sister must lead the family. The elder brother takes the father role for his siblings, and the elder sister takes the mother role. The income of respondents emerges as a pivotal factor in influencing the experience of domestic violence and child labor in this region. This study also reveals their daily working hours, and 81.5% of child laborers are working ten to twelve hours daily. The main reason for working is due to the family's low income.

This study agrees with the previous research by Shilongo (2021) that geographical areas and regions have a significant influence on child labor. The less regional development of socioeconomics will make a larger number of child laborers. This study disagrees with the previous study by ILO (2017), which described boys as having a greater risk of child labor than girls. The reason is that Myanmar has a larger number of females than males because there were 51.4 million of the population, according to the 2014 Myanmar Population and Housing Census, and 52% were women.

The binary logistic regression model shows that the respondent income, identification of townships, region (rural, urban), sex (male, female), the position of the respondents in their households, do their fathers have a job, income support the family expenditure have statistical significance at 5% level on experience in domestic violence of child labor. Kinds of domestic violence, income of the respondents, townships (region of residence), respondent position in the household, and family income are the important variables on experience in domestic violence by the random forests model. One of the random forest models is that it can analyze a larger number of predictor variables than the other two models (logistic regression and lasso regression). In the logistic lasso regression model, respondents' income is the important variable on experience in domestic violence or child labor. One of the advantages of lasso regression is that it can eliminate the useless variable/ unimportant variable by shanking the coefficient to zero. However, there are similar assumptions to standard logistic regression, and it needs a large enough sample size to ensure stable parameter estimates and reliable statistical inference. Thus, every model has unique strengths and weaknesses and produces diverse results. In brief, this paper provides not only the determinant of child labor in this region but also an overview of the implementation of three models and the feature selection capacity of these different models. Thus, this study can assist decision-makers and other interested parties in comprehending the dynamics and root causes of child labor in Myanmar, enabling them to establish more effective initiatives and regulations to address the problem.

Globally, child labor persists in formal and informal settings, necessitating comprehensive policies and robust law enforcement. Addressing this issue requires legal measures and a commitment to tackling root causes like poverty and unemployment. Implementation gaps in government policies demand further action. The Minimum Age Convention prohibits children under 14 from working and those under 18 from engaging in hazardous work. Despite government efforts to provide information on child labor, additional action is evident. This research study will contribute to the awareness of child labor and children's rights among working children, employers, and the community. It would bring about how household poverty and the country's economic conditions impact child labor. This study would be a voice of Myanmar child labor to the world and the Myanmar people to be aware of the children's rights and well-being for a better future.

VIIII. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The main limitations are

i. This study includes only the ages of 5-17 of children, and this cannot cover under five years old children because some children under five years are forced on the streets to sell flowers or drink water bottles.

ii. This study cannot cover disabled children and family workers, like childcare, cooking, cleaning, and shopping for their own houses/businesses.

iii. This study will only cover child laborers working in a stranger's shop or business.

iv. Another limitation is no response. There may be no response in this real world because they may be afraid of their boss, or there is no chance to answer/ make an interview with them or no time free or refuse to answer.

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