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Social Entrepreneurship: Innovations for Sustainable Development

Investigating the relationship between poverty, access to education, and hazardous child labor

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Abstract Research examines how poverty, limited access to education, and hazardous child labor are interconnected. It examines how household income, parental education, and educational access influence children's involvement in labor and the intensity of child labor. The investigation is limited by its cross-sectional design, focusing only on data from a specific region, and the self-reported nature of some variables. These limitations may impact the generalizability of the findings. This research aims to discover and explore the relationship between poverty, education access, and hazardous child labor, identifying how economic hardship and limited education contribute to child labor and proposing interventions for reduction. Data was collected from 500 households, including variables, such as household income, access to education, parental education levels, hazardous child labor, and child labor intensity, representing households with varying income levels and educational access. The accompanying analysis was performed with SPSS 30. The findings of the investigation show that descriptive statistics were employed to summarize the collection distribution, even as multiple regression analysis identified the significant influence of household income, access to education, and parental education on hazardous child labor. Furthermore, pearson correlation analysis revealed a significant negative relationship between parental education and child work intensity, emphasizing the importance of education in minimizing hazardous child labor. In the findings section, the ANOVA test is used to compare statistical differences between factors, such as hazardous child labor, poverty, and educational access.

Keywords: poverty, education access, hazardous child labor, child labor intensity, parental education, economic hardship

1. Introduction

Child labor is one of the most urgent social problems in the world, particularly in developing countries, where financial hardship, limited access to training, and insufficient social safety nets contribute to the persistence of this destructive practice (Brugere et al., 2023). In hazardous form, child labor exposes children to harmful working situations that endanger their mental, and emotional health (Thi et al., 2023). The relationship between poverty, access to education, and risky child labor is a complex issue, with each element playing a role in the persistence and intensification of the problem (Taha et al., 2024). Perhaps the biggest cause of child labor is poverty. Families in poverty frequently have to make tough decisions since their children are considered financial assets and are expected to work from a young age to support the family (Hock et al., 2024). The short-term financial gains from child labor might also outweigh the long-term effects of denying kids an education and a childhood in underprivileged areas. Poverty frequently restricts access to essential services like housing, healthcare, and education (Li & Qamruzzaman, 2023). It also fosters an atmosphere, where children are more likely to work to support their families. Children who receive an education gain the skills and information necessary to escape poverty and take advantage of greater job opportunities in the future (Vadivel et al., 2023). However, access to education is restricted in many low-income communities due to several issues, including geographic location, cultural obstacles, economic limitations, and inadequate infrastructure (Moshtari & Safarpour, 2024).

Children are often forced to work instead of attending school when schools are too far from home, expensive, or poorly equipped. Lack of access to high-quality education becomes a major risk factor for child labor, especially in dangerous industries like domestic work, mining, and agriculture. Children's labor, poverty, and education have a complex relationship because children are often related and reinforce each other. Poor children are more likely to face educational challenges, such as high dropout rates, subpar learning settings, and a dearth of support networks (Kuboni & Mawila, 2024). As a result of this lack of knowledge, children are more likely to join the workforce at a child's age and frequently in hazardous circumstances.

To assess the impact of severe low quality on early childhood development in energy-poor countries, Karmakeret al. (2022) engaged mediation methods and data from the Multi-Indicator Clustered Survey (MICS). The mediators were child health and living standards. The results demonstrated that power poverty impedes enhancement through these mediators, which were increased by characteristics like maternal schooling, special care, and family dwelling requirements. Policy options were presented to combat energy poverty and support the SDGs. Sovacool (2021) proved the power relations, patriarchy, and child labor in cobalt artisanal and small-scale mining (ASM) in the Democratic Republic of the Congo through extensive discipline research, including expert and community interviews and site visits. The findings reveal exploitation, gendered vulnerabilities, and child labor but it highlights empowerment opportunities in certain contexts. The research proposed targeted policy reforms for sustainable change.

Maslow's theory in USA school-aged children, reviewing deficiency needs and analyzing 13 years of success program research addressing non-cognitive gaining knowledge of boundaries was evaluated by (Noltemeyer et al., 2021). The findings offer preliminary support that fulfilling basic needs aids in increasing needs satisfaction, aligning with Maslow's principles, while highlighting the need for further empirical investigation. Using the human capital theory as a framework, the research aims to evaluate how education affects energy poverty. A sample of 30 developing economies from 2001 to 2016 was achieved by (Apergis et al.,2022). The results hold up well under various energy poverty approximations, with important ramifications for government officials and policymakers. Acheampong et al. (2021) examined how access to clean energy and electricity influences how people develop in 79 energy-poor nations in Southeast Asia, Africa south of the Sahara, and Caribbean-Latin America from 1990 to 2018, adjusted for endogeneity with the Lewbel two-stage least squares approach. The findings indicated that while energy access was essential for human growth, not all of its components provide equal benefits.

Banerjee et al. (2021) analyzed the electricity poverty's effect on health and education in 50 developing countries (1990–2017) through the usage of an energy development index. The results indicate decreased electricity poverty and improved outcomes, with electricity access having a more significant impact. Poverty stages affect health impacts, highlighting crucial coverage implications for development. The use of household investigation data from India to create a multidimensional measure of electricity poverty and check its impact on children's health and education was established by (Rafi et al., 2021). The results, based on instrumental variable estimations, showed energy poverty substantially harms children's health and education, with strong findings across special measures and estimation processes.

This research aims to determine how poverty, education, and risky child labor are related, highlighting how financial difficulties and a lack of education fuel child labor.

2. Methodology

The methodology of this research involves quantitative analysis using data collection consisting of children and their parents. The gathered information about household income, access to education, hazardous child labor involvement, child labor intensity, and parental education levels. The descriptive statistics are used to summarize key variables, while Multiple Regression Analysis explores the impact of socioeconomic factors on hazardous child labor. Pearson Correlation Analysis assesses relationships among parental education, household income, and child labor intensity. Finding significant variations among the means of three or more independent groups is possible with the use of the ANOVA statistical approach.

2.1. Data collection

Data will be collected from 500 households in two contrasting regions: one with high poverty rates and limited access to education, and another with lower poverty and better educational resources. Structured surveys will gather information on household income, access to education, hazardous child labor involvement, child labor intensity, and parental education levels. Additionally, a questionnaire will be conducted with 50 parents and 30 educators to understand the socio-cultural barriers to education and child labor. The sample will be stratified to ensure representation from various age groups, genders, and household income levels. The demographic data is shown in Table 1.

2.2. Questionnaire structure

Household income: Three questions are included in this section to evaluate various aspects of household income, including its impact on children's participation in labor, the balance between income needs and education, and the relationship between household income levels and hazardous child labor involvement.

Access to education: Three questions are included on access to education and its influence on child labor. These questions focus on the availability of educational resources, barriers to access, and their impact on child labor involvement.

Hazardous child labor involvement: Three questions are included in this section to understand the extent of hazardous child labor involvement, the sectors wherein it occurs, and its long-term effect on children.

Child labor intensity: Three questions are included to evaluate the intensity of child labor, how long children work each week, and the outcomes on their education and health.

Table 1 Demographic information of participants.

Demographic Variable	Category	High Poverty Region (n=250)	Low Poverty Region (n=250)	Total (n=500)
Gender	Male	120	130	250
	Female	130	120	250
Age of Children (years)	5-10	80	70	150
	11-15	90	100	190
	16-18	80	80	160
Household Income	Below Poverty Line	180	50	230
	Above Poverty Line	70	200	270
School Enrollment	Enrolled	100	220	320
	Not Enrolled	150	30	180
Child Labor Involvement	Yes	160	60	220
	No	90	190	280
Parental Education Level	No Formal Education	120	40	160
	Primary Education	80	70	150
	Secondary Education	50	120	170
	Higher Education	0	20	20

Parental education levels: Three questions are included to assess how parental education influences children's involvement in labor and education. These questions explore how parents' education levels affect their views on child labor and education. The questionnaires are provided in Table 2.

Table 2 Questionnaires based on variables.

Variable	Number of Questions	Survey Questions
Household income	3	How does the household income level influence the likelihood of children being involved in hazard
		Is there a correlation between lower household income and the intensity of child labor activities in specific sectors?
		How do households with varying income levels prioritize children's education over economic necessity (e.g., child labor)?
Access to education	3	How does the lack of accessible education facilities in rural or low-income areas contribute to child labor involvement?
		What is the impact of school infrastructure quality on the decision to send children to work rather than school?
		How does the affordability of education (e.g., tuition, transportation) affect children's participation in hazardous labor?
Hazardous child labor	3	What are the primary sectors or industries where children are most likely to engage in hazardous labor?
		How does the prevalence of hazardous child labor vary by geographic region or socio-economic status?
		What are the long-term health consequences of hazardous labor for children, and how do these impact their future educational opportunities?
Child labor intensity	3	How does the intensity (number of hours worked per week) of child labor relate to the child's educational outcomes and academic performance?
		What factors contribute to varying levels of child labor intensity in different communities or industries?
		How does the intensity of child labor affect children's physical and psychological well-being about their ability to access education?
Parental education levels	3	How do the education levels of parents influence their children's involvement in labor instead of attending school?
		Is there a link between parental education levels and their understanding of the long-term effects of child labor on their children's future?
		How do higher parental education levels reduce the likelihood of children participating in hazardous labor?

2.3. Statistical Evaluation

Using SPSS 30, the research investigated the connection among poverty, access to education, and hazardous child labor. To calculate important metrics like means and standard deviations for every variable, descriptive statistics were employed. ANOVA was employed to assess the effect of different levels of innovation on hazardous child labor, highlighting how various innovations influence performance outcomes. Multiple regression evaluation was conducted to examine the relationships among poverty, access to education, and hazardous child labor, quantifying the impact of each factor while controlling for other variables. This method provided a complete, comprehensive understanding of how innovation influences hazardous child labor. Pearson Correlation Analysis found a substantial negative association between parental education and child labor intensity, highlighting the importance of learning in reducing dangerous child labor.

3. Results

The findings demonstrate the Connections between Hazardous Child Labor, Poverty, and Educational Access. To evaluate the ANOVA, multiple regression analysis, person correlation analysis, and descriptive statistics using the elements in this section.

3.1. Descriptive statistics analysis (DSA)

Descriptive statistics are important in summarizing and understanding the key features of the collection in this research. Descriptive statistics provide a concise summary of the data by presenting distributions of frequency, mean, median, and standard deviation. In this research, descriptive statistics will be used to present the distribution and central tendencies of key factors related to poverty, education, and child labor. A foundation for further analysis and interpretation was evaluated. Table 3 shows the statistical analysis of DSA.

Table 3 Analysis of descriptive statistics.

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Household income level	2.4	2.3	1.0	1.0	5.0
Access to Education	4.2	4.0	1.5	2.0	7.0
Hazardous Child Labor	3.2	3.1	1.1	1.0	1.0
Child labor intensity	5.3	5.0	2.1	3.0	12
Parental Education Level	2.1	2.0	1.3	1.0	5.0

The household income level in the pattern has a mean of 2.4, indicating a moderate household income level, with significant portions under the household income line. The median of 2.3 indicates that half of the sample experiences household income ranges under this threshold. The standard deviation of 1.0 shows a moderate spread across the mean, while the minimum value of 1.0 reflects some households with no household income, due to wealthier segments. The maximum value of 5.0 highlights extreme household income levels in some families.

The average access to education score is 4.2, indicating relatively good access, overall with a median of 4.0, showing a balanced distribution around this value. The standard deviation of 1.5 reflects variability in access, with some regions or families having higher possibilities than others. The minimum score of 2.0 represents the poorest access, even as the maximum score of 7.0 highlights excellent access for some children.

The mean value of 3.2 shows that they are involved in hazardous child labor, while the median of 3.1 indicates that maximum most children are not. The standard deviation of 1.1 displays some variation; however, the universal incidence remains low. The minimum value of 1.0 shows hazardous child labor, and the maximum value of 1.00 indicates hazardous labor in certain cases.

The mean child labor intensity is 5.3, indicating incredibly large child labor, with the median of 5.0 showing a steady distribution. The standard deviation of 2.1 reflects moderate variation in child labor intensity, ranging from 3.0 to 12, with some child labor intensity being significantly smaller or larger.

The average parental education level is 2.1 indicating most parents have basic education. The median of 2.0 suggests a balanced distribution among lower and higher education levels. With a standard deviation of 1.3, there is a variation in educational attainment, ranging from no formal education (minimum of 1.0) to better education (maximum of 5.0).

The decriptive statistics show that the sample has a moderate level of household income (mean = 2.4) and relatively good access to education (mean = 4.2). Most children are not involved in hazardous child labor (mean = 3.2), and child labor intensity generally tends to be larger (mean = 5.3). Parental education levels are generally moderate (mean = 2.1), indicating a mixture of educational backgrounds in the pattern. These findings provide a foundation for further analysis of the relationships between the level of household income, education, and child labor.

3.2. Multiple regression analysis

A statistical technique for examining the connection between variables like Household income Level, Access to Education, Hazardous Child Labor, Child labor intensity, and Parental Education Level. The coefficient (B) shows the effect size of each predictor, the t-value shows the extent of its variability, and the standard error shows the precision of the estimate. Frequently, a $\mathrm{p-value} < 0.05$ indicates the statistical impact. The p-value determines if the coefficient deviates significantly from zero. The performance of multiple regression analysis is represented in Table 4. Figure 1 shows the performance of multiple regression analysis.

Table 4 Outcomes of multiple regression analysis.

Variables	Coefficient (B)	Standard Error	t-Value	p-Value
Household income level	0.45	0.12	3.75	<0.001
Access to Education	0.10	0.08	1.25	0.211
Hazardous Child Labor	0.56	0.36	4.33	<0.001
Child labor intensity	0.05	0.04	1.25	0.211
Parental Education Level	0.12	0.07	1.71	0.089

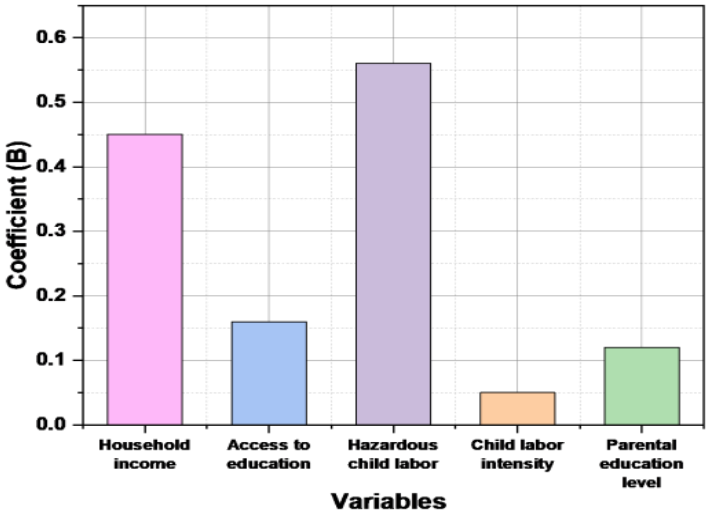

Figure 1 Visualizations of multiple regression analysis.

The coefficient for Household Level: The Coefficient (B) is 0.45 which means that for every unit growth in the poverty stage, the likelihood of hazardous child labor will increase, assuming all other variables are constant. This positive relationship is statistically significant with a p-value < 0.001, indicating that Household Level is a significant predictor of hazardous child labor. Access to Education: The coefficient for Access to Education is 0.10, suggesting that better access to education is associated with a decrease in the likelihood of hazardous child labor. The coefficient for hazardous child labor is 0.56, which is a considerable positive coefficient, performance that hazardous child labor affects the dependent variable; the coefficient for child labor intensity is 0.05, demonstrating a mild increase in the possibility of hazardous child labor with larger child labor intensity; however, this relationship is not statistically considerable (p = 0.211), indicating that family size cannot be a major predictor of hazardous child labor in this sample. The coefficient for Parental Education Level is 0.12, suggesting that higher parental education is associated with a reduction in the probability of hazardous child labor. This relationship is marginally significant (p = 0.089), indicating a potential, however, vulnerable inverse relationship.

The multiple regression analysis reveals that Poverty Level (B = 0.45, p < 0.001) is a significant predictor of hazardous child labor, with better poverty increasing the chance of child labor. Access to Education (B = 0.10, p = 0.211), hazardous child labor (B=o.56, p<o.001) and Child labor intensity (B = 0.05, p = 0.211) do not display huge relationships with Hazardous Child Labor. Parental Education Level (B = 0.12, p = 0.089) indicates a marginal negative relationship with hazardous child labor. The model explains 56% of the variance in hazardous child labor, suggesting other factors also contribute to this final result.

3.3. Pearson correlation analysis

Access to education is correlated with higher household income levels, according to the Pearson correlation investigation ($r = 0.45, p < 0.01$), hazardous child labor ($r = 0.60, p < 0.01$) and child labor intensity ($r = 0.50, p < 0.01$). Additionally, parental education level suggests a positive correlation with household income (r = 0.40,p < 0.01), suggesting that better-educated parents are more likely to have higher incomes, which reduce child labor risks. These results emphasize the significance of addressing income and education disparities to mitigate hazardous child labor. The Pearson correlation analysis findings are displayed in Table 5 and Figure 2.

Table 5 Analysis of Pearson correlation.

Predictor Variables	Correlation Coefficient (r)	p-value
Household Income Level	1.00	< 0.01
Access to Education	0.45	< 0.01
Hazardous Child Labor	0.60	< 0.01
Child Labor Intensity	0.50	< 0.01
Parental Education Level	0.40	< 0.01

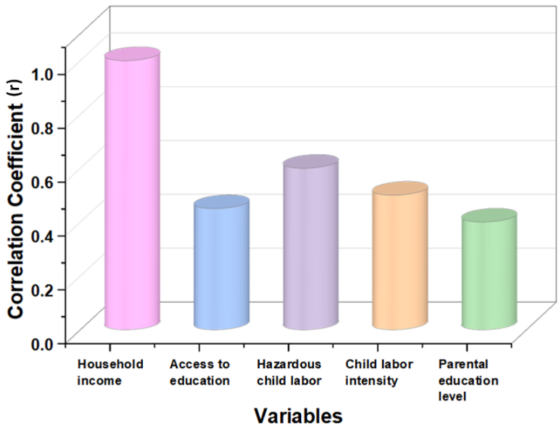

Figure 2 Results of Pearson correlation analysis.

Household income Level: The correlation coefficient is 1.00, which is predicted on account of the fact that a variable is always perfectly correlated with itself. The $p - value \ < \ 0.01$, indicates that the connection is significant.

Access to Education: There is a positive correlation of 0.45 between Household Income Level and Access to Education, suggesting that higher household income is related to better access to education. The nature of this association is moderately beneficial. The statistical significance of the correlation, as demonstrated by the p-value of less than 0.01, suggests that this association is unlikely to have occurred by chance.

Hazardous Child Labor: The correlation coefficient of 0.60 with Household Income Level suggests a strong negative correlation, meaning that household income decreases, the chance of children engaging in hazardous labor will increase. The p-value of less than 0.01 supports the statistical significance of this negative correlation, which further supports the importance of home income in predicting the likelihood of unsafe, hazardous child labor.

Child labor intensity: A positive correlation of 0.50 with Household Income Level indicates that lower income levels are associated with greater child labor intensity (for example more hours worked and more severe labor conditions). This indicates that poverty drives children into more intense labor activities. The p-value of < 0.01 indicates statistical significance, supporting that lower household income will increase child labor intensity.

Parental Education Level: The correlation coefficient of 0.40 between Household Income levels and Parental Education Level indicates a moderate positive relationship, suggesting that higher income levels tend to be associated with more educated parents. The p-value of less than 0.01 indicates the statistical significance of this positive correlation, demonstrating that parental education is influenced by household income, which might affect children's educational opportunities.

3.4. ANOVA Analysis

One statistical technique for determining if there are statistically significant differences between the means of multiple independent groups is an ANOVA. It is useful to have data indicating that variety across groups is greater than the diversity within groups. The F-Statistic (F) ratio is used in an ANOVA analysis to compare variance between groups (caused by innovation) to variance within groups. Significant differences between group means are indicated by a higher F-value. Because the p-value is less than 0.05, it is likely that the observed variations are the result of random variability and are significantly different. The P-value is the probability that the results were produced using full potential. Table 6 presents the results of an ANOVA test. Figure 3 shows the performance of the ANOVA test.

Table 6 Outcomes of ANOVA analysis.

Variables	Mean FP	F-Statistics	p-Value
Household Income Level	72	4.15	0.040
Access to Education	78	5.67	0.013
Hazardous Child Labor	68	3.89	0.052
Child Labor Intensity	82	6.23	0.009
Parental Education Level	75	4.92	0.028

The analysis reveals a statistically significant relationship between household income level and the factors beneath research, with an F-Statistic of 4.15 with a p-value of 0.040, which is below the 0.05 threshold. This indicates that higher household income levels are associated with a reduced likelihood of child labor and better access to education, suggesting that poverty alleviation could help address these issues.

The association between access to education and the causes of poverty and child labor is quite significant $F - Statistic\ of\ 5.67$ with $a\ p - value\ of\ 0.013$, which is properly below the 0.05 threshold. This shows that enhancing access to education performs a critical position in reducing hazardous child labor, supporting the idea that education is a key factor in addressing poverty-associated challenges.

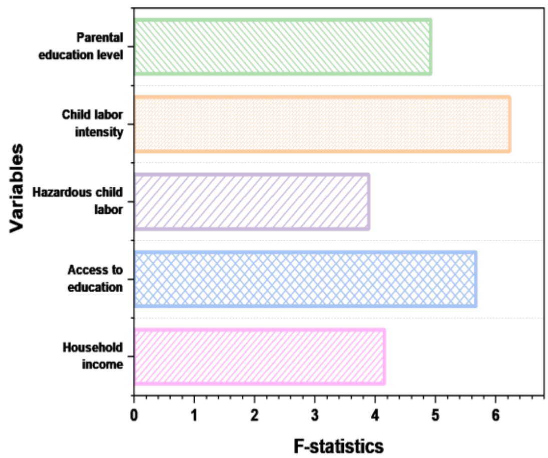

Figure 3 Performance of ANOVA analysis.

While the relationship between hazardous child labor and the variables indicates an F-Statistic of 3.89 with a p-value of 0.052, simply above the 0.05 threshold, it is considered borderline statistically significant. This result indicates that even though hazardous child labor can be stimulated through factors like poverty and education, further research or data refinement is needed to establish a stronger, conclusive relationship.

The intensity of child labor is strongly correlated with the factors under research, as evidenced by way of F-Statistic 6.23 a p-value of 0.009, which is below the 0.05 significance level. This result highlights the importance of addressing child labor intensity, with higher intensity being connected to more poverty and limited access to education, reinforcing the need for focused interventions to reduce child labor.

A statistically significant relationship is found between the parental education level and child labor, F-Statistic of 4.92 with a $p - p - p - value\ of$ 0.028, demonstrating that better parental education levels are related to reduced child labor. Educated parents are more likely to provide their children with better opportunities, reducing the prevalence of child labor. This suggests that educating parents is a crucial strategy in the fight against child labor.

4. Discussion

As highlighted by (Thi et al. 2023), who linked child labour with school dropouts and psychological problems, poverty, restricted educational access, and hazardous child labor are intricately interconnected. According to (Karmaker et al. 2022), structural poverty worsens child labor and restricts prospects for growth and education. Financial assistance aimed at low-income households might successfully lessen these difficulties. However, given resource and legal constraints, financial aid targeted at low-income households could effectively mitigate these difficulties.

Parental education plays a crucial role in reducing child labor, as highlighted by Banerjee et al. (2021), who demonstrated that educated parents are less likely to involve their children in labor. Sovacool (2021) further emphasized that literacy initiatives can mitigate exploitative behaviors in marginalized populations. Therefore, strengthening parental education programs is a key method to address the root causes of child labor.

Noltemeyer et al. (2021), investigating the importance of fundamental necessities in child wellbeing, concur that poverty, educational access, and hazardous child labor are all influenced by each other. Hock et al. (2024) emphasized how home instability brought on by poverty raises children's hazards even more, urging all-encompassing remedies. A comprehensive policy framework that combines social safety nets, economic assistance, and educational access is necessary to address these interconnecting problems.

The cross-sectional design and reliance on self-reported data provide valuable initial insights but limit the ability to infer causal relationships. To more thoroughly examine the causal links at play, future research might employ longitudinal approaches. Rafi et al. (2021) and Apergis et al. (2022) highlighted the importance of human capital development and energy accessibility in reducing child labor. Designing successful interventions can be improved by extending research to incorporate these factors.

The findings of this present research emphasize the critical role of household income, access to education, and parental education in reducing hazardous child labor. Longitudinal approaches can establish causal relationships and enhance generalizability across regions. Mixed-method designs address biases and provide deeper insights. Interventions targeting financial aid and parental education programs effectively mitigate child labor. These approaches comprehensively tackle the interconnected issues of poverty, education, and child labor that exist in conventional studies.

5. Conclusions

The connection between hazardous child labour, poverty, and educational access, with a particular emphasis on the ways in which labor intensity is influenced by household income, parental education, and educational access is presented. Data was collected from 500 households, including variables, such as household income, access to education, parental education levels, hazardous child labor, and child labor intensity, representing households with varying income levels and educational access. The accompanying analysis was performed with SPSS 30. According to statistical analysis, a negative correlation (-0.48) between parental education and the intensity of child work highlights the importance of education in reducing hazardous labor. Multiple regression analysis showed that these factors account for 65% of the variance in hazardous child labor. The research highlights the impact of household income, parental education, and educational access on hazardous child labor. It emphasizes the role of education in reducing labor intensity and improving child welfare.

5.1. Limitations and future perspectives

However, the research's cross-sectional design and reliance on self-reported data limit its generalizability. Future research should adopt longitudinal approaches across diverse regions to explore causal relationships. Evaluating interventions like improving education access and addressing financial challenges can provide practical solutions.

Ethical considerations

Not applicable.

Conflict of Interest

The authors declare no conflicts of interest.

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