Neutrosophic Sets and Systems, Vol. 66, 2024

University of New Mexico

Child Labor, Informality, and Poverty: Leveraging Logistic Regression, Indeterminate Likert Scales, and Similarity Measures for Insightful Analysis in Ecuador

Arnaldo Vergara-Romero[1], Guido Macas-Acosta[2], Fidel Márquez-Sánchez[3], Orlando Arencibia-Montero[4]

[1]Universidad Ecotec, Km 13.5 vía Samborondón, Samborondón-Ecuador., E-mail: avergarar@ecotec.edu.ec

[2]Universidad Ecotec, Km 13.5 vía Samborondón, Samborondón-Ecuador., E-mail: gmacas@ecotec.edu.ec

[3]Universidad Espritu Santo Km 2.5 vía Samborondón, Samborondón-Ecuador, fmarquez@uees.edu.ec,

[4]VSB-Technical University of Ostrava 17. listopadu 2172/15. 708 00 Ostrava-Poruba. Czech Republic. E-mail: orlando.arencibia@vsb.cz

* Correspondence: gmacas@ecotec.edu.ec

Abstract.

The paper presents a comprehensive analysis of child labor in Ecuador, employing advanced statistical tools like logistic regression, neutrosophic Likert scales, and similarity measures to deepen the understanding of this social issue. The integration of these methodologies allows for a nuanced assessment of the various socio-economic factors contributing to child labor. By capturing the uncertainty in human responses, the research highlights the complex interplay between poverty, household income, education levels, and labor types on the incidence of child labor. Key findings suggest that rural location, the age of the child, and the informal nature of the head of the household's work are the most significant predictors of child labor. Notably, parental education appears to have a less direct influence. Despite various efforts, including government monetary transfers through programs like the BDH, child labor persists, indicating the need for more targeted interventions.The paper proposes future research to extend these models to a broader demographic and geographic data set, emphasizing the potential for these methods to be applied to a variety of social issues. The development of computational tools to automate neutrosophic analysis could greatly benefit large-scale studies, potentially aiding policymakers in designing more effective interventions for vulnerable populations.

Keywords: Child Labor, Logistic Regression, Neutrosophic Scales, Indeterminacy

1. Introduction.

Child labor continues unabated globally, exacerbated by increasing poverty, informality, inequality, and insufficient governmental support, particularly in developing nations. According to the International Labor Organization (ILO), over 200 million children are involved in labor, depending on definitions and data sources [1]. In the poorest countries, more than one in five children is involved in child labor [2]. Ecuador presents a concerning scenario where one in ten children and adolescents are working, with 85% of these residing in rural areas. This study aims to explore how the distribution of labor activities among minors in Ecuador varies over time in response to household income constraints and minimal state intervention to ensure education access and revitalize the economy in areas vulnerable to child labor.

Numerous studies have identified poverty as a critical factor influencing child labor dynamics, potentially worsened by ineffective state policies [3]. Research also delves into the types of work minors engage in, the impact on their education and health, and the associated externalities [4]. Some argue that government economic

compensations, despite being intended to alleviate poverty and hence reduce child labor, have been insufficient [5][6]. In Ecuador, the Bono de Desarrollo Humano (BDH), a monetary transfer to impoverished and unemployed heads of households or single mothers with minor children, ranges from $50 to $260 monthly, which has not substantially resolved the issue [7]. Conditional Transfer Programs (CTPs) across Latin America aim to mitigate poverty and child labor, showing improvements in income, food consumption, and access to education and health, thus reducing child labor and empowering mothers [8]. Edmonds & Schady [9] found that such transfers in Ecuador significantly reduce child labor, including paid employment, particularly among children who were students.
Factors driving children into labor are predominantly linked to poverty, including family income levels, credit restrictions, and lack of access to microcredit, among others Basu [10]. Furthermore, minimal state assistance and economic crises exacerbate family members' reliance on "family savings," intensifying unpaid domestic work, primarily performed by women and girls. However, non-poverty-related factors, such as parental perspectives, education level, household dynamics, proximity to schools, and educational costs, play a significant role [11].

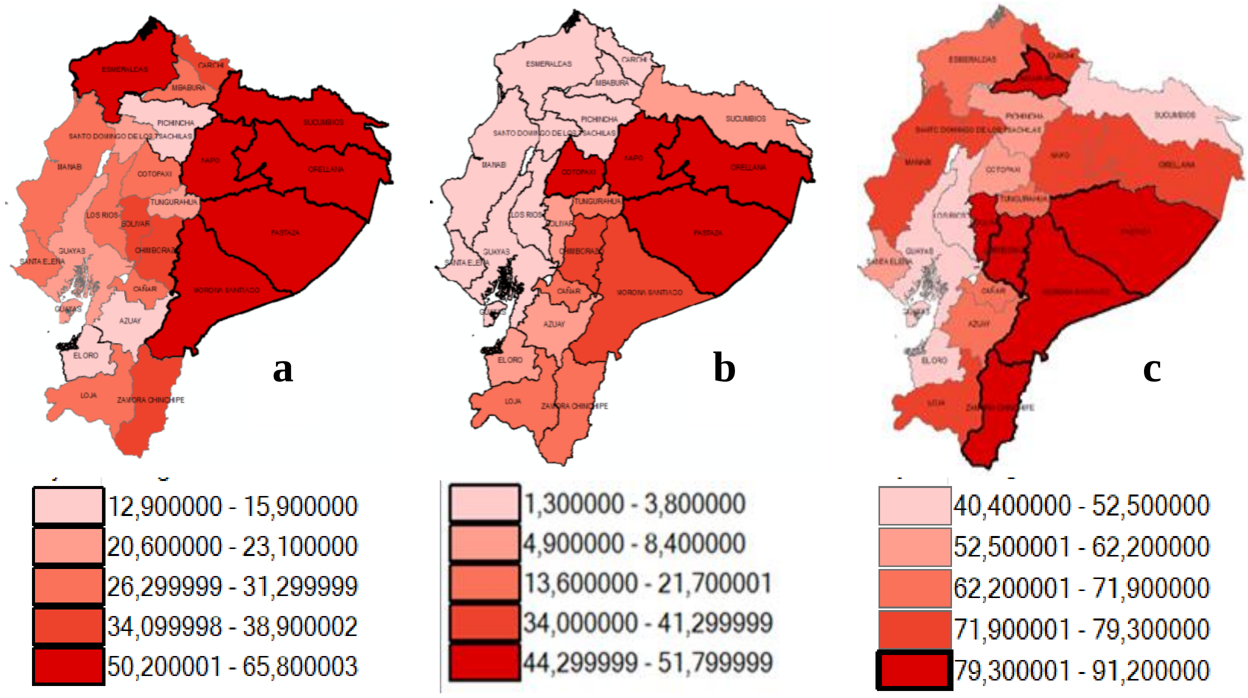

Figure 1. Percentage of Population by Province of Ecuador under poverty (a), with child labor (b) and informal work (c). [12].

In the paper of child labor in Ecuador, logistic regression [13], neutrosophic Likert scales [14] , and similarity measures[15] are employed as advanced statistical and analytical tools to identify and quantify the factors influencing these social issues. Logistic regression is used to model the probability of binary events occurring, such as whether a child participates in labor activities or not, based on a set of predictor variables, such as family income level, access to education, and housing conditions. On the other hand, neutrosophic Likert scales capture the uncertainty and indeterminacy in respondents' perceptions and opinions on the causes and consequences of child labor and poverty, facilitating a more nuanced assessment of attitudes and experiences. Similarity measures are employed to determine the relationship between variables that influence child labor. By analyzing how closely related these variables are, researchers can identify common patterns and factors contributing to child labor.
This method allows for a nuanced understanding of the complex interplay between socioeconomic conditions, family characteristics, and educational access, among others, in influencing the likelihood of children entering the workforce. Through the use of similarity measures, it becomes possible to cluster similar variables and discern which variables most significantly impact child labor, aiding in the development of targeted interventions and policies to address this issue effectively. By combining these approaches, researchers can gain deeper insights into the complex dynamics underlying child labor and poverty in Ecuador, which is crucial for designing more effective public policies specifically targeted to the needs of vulnerable populations.

2. Preliminaries

2.1 Logistic Regesion Model

The logit model represents the relationship between the likelihood of an event occurring and its independent factors. The following serves as the basis for deriving the logistic function used for modelling the probability that a specific event will occur, which in this case is whether or not the child or adolescent works.

The following is an example of how to write a logit function [16]:

$$logit(l) = log\left(\frac{P}{(1-P)} = Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \mu_i\right) \quad (1)$$

In this case, P represents the likelihood that an event will occur and the likelihood that the event will occur. At the same time, Z may be considered a linear combination of the independent variables and their coefficients. Equation 2 mentioned above may be solved further to arrive at the following function, which can then be used to estimate the probability of the event[17].

$$log\left(\frac{P_i}{(1-P_i)}\right) = logit(P) \quad (2)$$

The logit model's capacity to represent the relationship between the likelihood of an event and its independent factors provides a robust framework for statistical analysis in various fields, including the study of child labor. However, while logistic regression can offer insights into the probabilities associated with certain outcomes, it does not inherently determine causality. This is where the concept of neutrosophy and the use of indeterminate Likert scales[18] become particularly valuable.

2.2 Indeterminate Likert Scales and Similarity Measures

The foundational concepts of neutrosophic set [19] and its application through indeterminate Likert scales and similarity measures form a pivotal framework for addressing uncertainty and indeterminacy in various fields. Neutrosophic Likert scales extend traditional Likert scales by incorporating degrees of indeterminacy, allowing respondents to express not just agreement or disagreement but also uncertainty regarding statements or questions. This nuanced approach to survey responses captures a broader spectrum of human perception and opinion, making it invaluable for research that deals with subjective information. Concurrently, neutrosophic similarity measures evaluate the degree of similarity between entities represented by neutrosophic sets, facilitating the comparison and clustering of data with inherent uncertainties.

These concepts are crucial for the advanced analysis of complex systems where traditional binary logic falls short, enabling researchers to delve deeper into the intricacies of human cognition and decision-making processes.

Definition 1 ([19]). The *Single-Valued Neutrosophic Set* (SVNS) N over U is $A = \{< x;\ T_A(x), I_A(x), F_A(x) >: x \in U\}$, where $T_A: U \to [0,1]$, $I_A: U \to [0,1]$, and $F_A: U \to [0,1]$, $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

Definition 2 ([20]). The *refined neutrosophic logic* is defined such that: a truth T is divided into several types of truths: $T_1, T_2, \ldots, T_p$, I into various indeterminacies: $I_1, I_2, \ldots, I_r$ and F into various falsities: $F_1, F_2, \ldots, F_s$, where all $p, r, s \geq 1$ are integers, and $p + r + s = n$.

Definition 3 ([19]). A *triple refined indeterminate neutrosophic set* (TRINS) A in X is characterized by positive $P_A(x)$, indeterminacy $I_A(x)$, negative $N_A(x)$, positive indeterminacy $I_{P_A}(x)$ and negative indeterminacy $I_{N_A}(x)$ membership functions. Each of them has a weight $w_m \in [0,1]$ associated with it. For each $x \in X$, there are $P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x) \in [0,1]$, $w_P^m(P_A(x)), w_{I_P}^m(I_{P_A}(x)), w_I^m(I_A(x)), w_{I_N}^m(I_{N_A}(x)), w_N^m(N_A(x)) \in [0,1]$ and $0 \leq P_A(x) + I_{P_A}(x) + I_A(x) + I_{N_A}(x)(x) + N_A(x) \leq 5$. Therefore, a TRINS A can be represented by $A = \{\langle x;\ P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x)\rangle | x \in X\}$.

Let A and B be two TRINS in a finite universe of discourse, $X = \{x_1, x_2, \ldots, x_n\}$, which are denoted by:

$A = \{\langle x;\ P_A(x), I_{P_A}(x), I_A(x), I_{N_A}(x), N_A(x)\rangle | x \in X\}$ and $B = \{\langle x;\ P_B(x), I_{P_B}(x), I_B(x), I_{N_B}(x), N_B(x)\rangle | x \in X\}$,

Where $P_A(x_i), I_{P_A}(x_i), I_A(x_i), I_{N_A}(x_i), N_A(x_i), P_B(x_i), I_{P_B}(x_i), I_B(x_i), I_{N_B}(x_i), N_B(x_i) \in [0,1]$, for every $x_i \in X$. Let w_i(i = 1, 2,...,n) be the weight of an element x_i (i = 1,2,...,n), with $w_i \geq 0$ (i = 1,2,...,n) and $\sum_{i=1}^{n} w_i = 1$.

The weighted distance for generalized TRINS is defined as ([19, 21]):

$$d_\lambda(A,B) = \left\{\frac{1}{5}\sum_{i=1}^{n} w_i \left[|P_A(x_i) - P_B(x_i)|^\lambda + \left|I_{P_A}(x_i) - I_{P_B}(x_i)\right|^\lambda + |I_A(x_i) - I_B(x_i)|^\lambda + \left|I_{N_A}(x_i) - I_{N_B}(x_i)\right|^\lambda + |N_A(x_i) - N_B(x_i)|^\lambda\right]\right\}^{1/\lambda} \quad (3)$$

Where $\lambda > 0$.

Definition 9: ([22,23]) Let $A, B \in \mathcal{N}(X)$ where $X = \{x_1, x_2, \cdots, x_n\}$, then a measure of similarity between sets A and B is determined by calculating the distance between them, which reflects their convergence or divergence within a neutrosophic framework calculated by :

$$S^1(A,B) = \frac{1}{1+d(A,B)} \quad (4)$$

Such that $d(A,B)$ is a distance function between the two single-valued neutrosophic sets.

Let us recall that the distance function satisfies the following axioms $\forall A, B, C \in \mathcal{N}(X)$:

(1) $d(A,B) \geq 0$ and $d(A,B) = 0$ if and only if $A = B$,

(2) $d(A,B) = d(B,A)$,

(3) $d(A,C) \leq d(A,B) + d(B,C)$.

The Indeterminate Likert Scale is formed by the following five elements:
– Negative membership,
– Indeterminacy leaning towards negative membership,
– Indeterminate membership,
– Indeterminacy leaning towards positive membership,
– Positive membership.
These values substitute the classical Likert scale with values (Figure 2):
–Strongly disagree,
– Disagree,
–Neutral,
– Agree,
–Strongly agree.

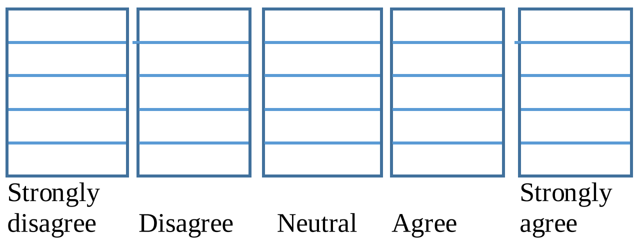

Figure 2. Visual representation of Indeterminate Likert Scale

Respondents are asked to give their opinion on a scale of 0-5 about their agreement in each of the possible degrees, which are “Strongly disagree”, “Disagree”, “Neutral”, “Agree”, “Strongly agree”, for this end, they were provided with a visual scale like the one shown in Figure 2.

3. Material and Methods

The information in this research comes from the National Survey of Employment, Unemployment, and Underemployment (ENEMDU), carried out by the Ecuadorian Institute of Statistics and Census (INEC) in December 2022. The incidence of child labor is calculated with the questions that determine the occupancy condition (questions 20, 21, and 22) in the reference week. The initial data was processed and filtered for the most efficient and consistent estimation. The database was configured with a two-stage, stratified, and cluster sampling design to obtain population estimators. Then, the children and adolescents between the ages of 5 and 17 who were or were not working during the survey were selected. To this is added additional information on the characteristics of the heads of the household, such as income, years of education, area of residence, gender, and age, among others. The employment income used in this investigation will equal or less than $3,500. 95% of entrepreneurs register payments of fewer than 1,200 dollars, which is why the barrier of 3,500 was located, as is also done by the Central Bank of Ecuador in its poverty and income reports [24]. Thus, there was a sample size of 64,847 observations.

This research used a logistic regression estimate considered as a tool to analyze data where there is a categorical response variable with two levels, in this case, if the minor works or not, also if he is poor or not poor, whether or not the head of household studied, among others.

The results of applying the econometric model (Logit) are exposed concerning the factors that influence child labor in 2022, and it is essential to mention that the target population is children aged 5 to 17 years. Age, regardless of their sex, area, ethnic self-identification, or any other factors inferring the model. The independent variables used for the model are the following:

Table 1. Description of the independent and dependent variables.

Variables	Description	Type	Scale
Age Range	1 (5 to 11 years) 2 (12 to 14 years) 3 (15 to 17 years)	Quantitative	Ordinal
Head of Household Income	Income	Quantitative	Ordinal
Jetrainfo	0 (Formal) 1 (Informal)	Qualitative	Nominal
Educajeho	Years	Quantitative	Ordinal
Zone	0 (Urban) 1 (Rural)	Qualitative	Nominal
Gender	0 (Women) 1 (Man)	Qualitative	Nominal
Pobhogti	0 (Not poor) 1 (Poor)	Qualitative	Nominal

With the complex variables, the Logit model is carried out, as established by the maximum likelihood methodology, as expressed below:

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1(rangodad) + \beta_2(ingrejeti) + \beta_3(jetrainfo) + \beta_4(educajeho) + \beta_5(pobhogti) + \beta_6(zona) + \beta_7(sexo) + \mu_i \quad (5)$$

Where:

$L_i = \ln\left(\frac{P_i}{1-P_i}\right)$ The logarithmic probability that a child and adolescent is in a situation of child labor in the country in 2022.

$X_1 \dots X_7$: Social, economic, and demographic factors.

β_0: Logit model constant.

$\beta_1 \dots \beta_7$: Model earrings.

μ_i: Stochastic error.

It is essential to mention that these variables used for the model were transformed using the statistical package Stata 17. In addition, this model is not intended to look for a causal relationship but rather to see the degree and direction of association of a set of dimensions versus the probability of choosing among the options presented.

The influence of various variables on child labor was assessed by consulting a panel of five experts using indeterminate Likert scales. To quantify the level of agreement or disagreement, responses were aggregated as follows: the degree of "Strongly agree" was derived from the sum of truth by $\sum_{i=1}^{5} T_A(x_i)$, the degree of “Agree” by $\sum_{i=1}^{5} I_{T_A}(x_i)$, the degree of “Neutral” by $\sum_{i=1}^{5} I_A(x_i)$, the degree of “Disagree” by $\sum_{i=1}^{5} I_{F_A}(x_i)$, and the degree of “Strongly disagree” by $\sum_{i=1}^{5} F_A(x_i)$.

Each of these sums was then averaged by dividing by 5 and scaled to percentages.

The questions posed to experts were structured as follows:

Q1: To what extent do you agree that the age range influences child labor?

Q2: How much do you believe the income of the head of the household influences the incidence of child labor?

Q3: How strongly do you agree that the type of work (formal vs. informal) affects children's participation in child labor?

Q4: To what degree do you think the level of education influences the likelihood of a child being involved in child labor?
Q5: Do you agree that the area of residence impacts the incidence of child labor?
Q6: Do you consider that the gender of the child significantly influences child labor?
Q7: To what extent do you believe poverty impacts child labor?

The distance between TRINS (Triple Refined Indeterminate Neutrosophic Sets) was calculated using the Euclidean distance formula, providing a quantitative measure of the closeness or similarity(4) between the sets of responses for each question. This methodological approach allows for a nuanced analysis of expert opinions on factors affecting child labor, incorporating the complexity and uncertainty inherent in social phenomena[19].

4. Results

The factor that most affects child labor is the location of the family in rural areas(Table 2), followed by the minor's age and then by the everyday work of the head of the household. It can be noted that parental education does not influence child labor and that the average years of study for people who live in rural areas is eight while those who live in urban areas are ten years. The results imply that most parents do not finish high school.

In short, it can be described that if the little one lives in a rural area, the probability of working increases by 10.5%, and each time he approaches the age of 15, his options to work gain by 4%. Further, it can also be noted that if the father works informally, the probability that minors work is 2.2%. In this case, there is no significant difference if the head of the household is male or female, as seen in the table of logit model estimation.

Table 2. Logit Model estimation.

	Parameter	Standard Error	t	p-value	Odd Ratio	Marginals Effects dy/dx	p-value
Constant	**-5,41**	0,144	-37,711	**0,000**	**0,00**		
trinfjeti	**0,51**	0,039	13,161	**0,000**	**1,67**	**2,2%**	0,000***
edujehoti	**-0,02**	0,004	-3,852	**0,000**	**0,98**	**0,0%**	0,000***
pobreti	**0,21**	0,038	5,406	**0,010**	**1,23**	**1,0%**	0,000***
sexti	**0,35**	0,031	11,380	**0,000**	**1,43**	**1,5%**	0,000***
ruralti	**1,72**	0,035	49,486	**0,000**	**5,57**	**10,5%**	0,000***
lingjehogati	**-0,04**	0,020	-1,826	**0,068**	**0,96**	**-0,2%**	0,0678*
ranedad	**0,98**	0,019	50,719	**0,000**	**2,65**	**4,1%**	0,000***
Statistical evaluation							
R-squared	**20,4%**						
Information Criteria							
AIC	29743						
BIC	29816						

However, the situation may increase in areas with higher levels of informality, and the population is concentrated in rural areas, such as in various provinces of the Oriente and the Sierra. Moreover, unpaid economic activities focus on farms, plots, and even family businesses, where child labor increases among the poorest households with children over 14 years of age and decreases among the least imperfect.

On the other hand, for unpaid domestic workers, where due domestic services are also included, more than 200,000 children are working, and more intensely, those between 12 and 14 years of age. The result can be a reason for reduced academic performance or delays in school or secondary school processes, especially in rural areas, which, on average, have two fewer years of schooling than urban areas.

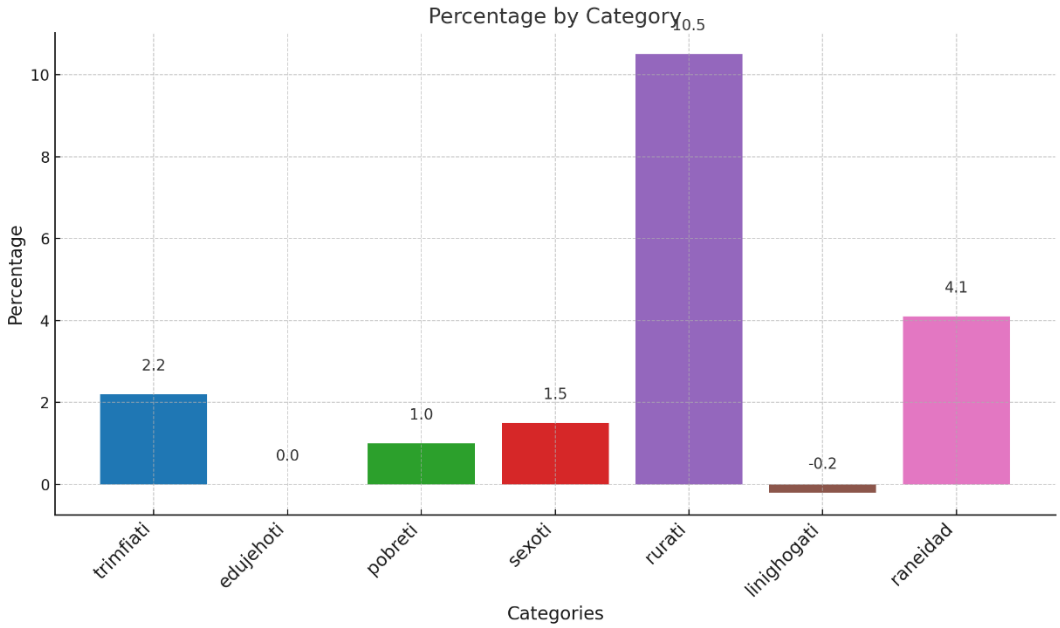

Figure 3. Logistic Regression Outcomes: Impact of Socioeconomic Variables on Child Labor

Experts were requested to evaluate the impact of each variable on child labor through the use of Likert-type scales, and Figure 3 showcases the gathered responses.

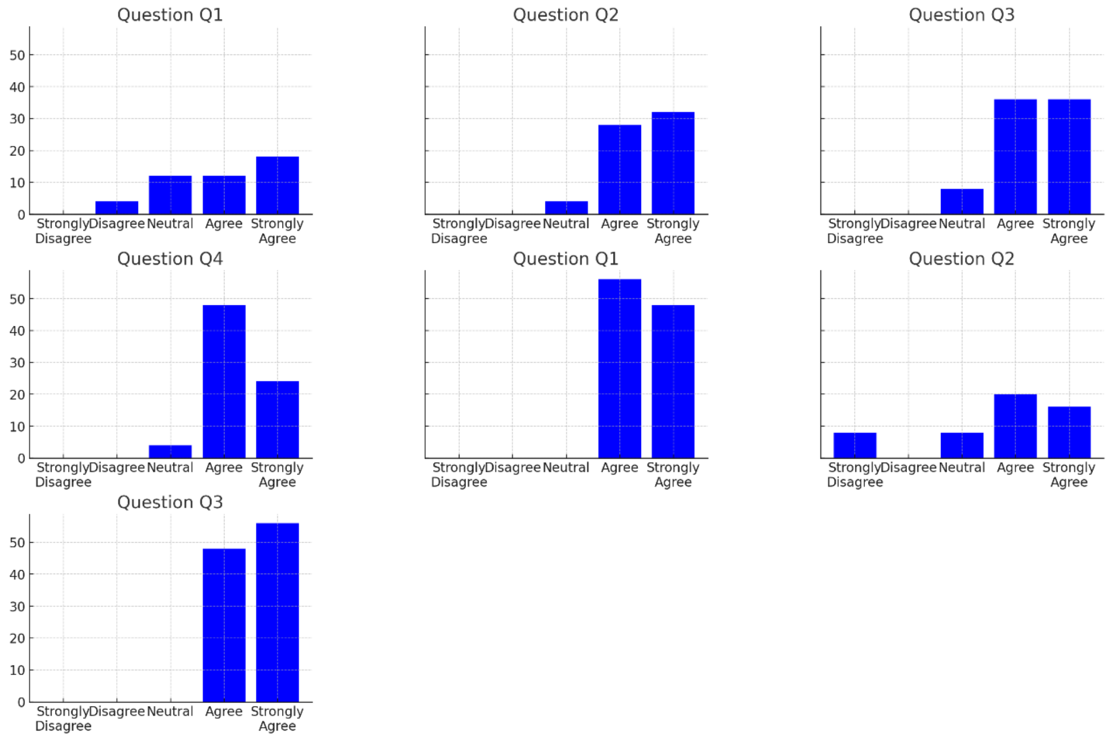

Figura 3. Neutrosophic Likert Scale Analysis

The results indicate varied perceptions on factors influencing child labor:

- Age Range: There's a general agreement that age range influences child labor, with the majority falling in the 'Agree' to 'Strongly Agree' categories.
- Household Income: The belief that the head of household's income affects child labor incidence is strong, as reflected by the higher number of respondents in the 'Agree' and 'Strongly Agree' responses.

- Type of Work: There's a strong consensus that the type of work, whether formal or informal, has a significant effect on child labor, with most responses again in the 'Agree' and 'Strongly Agree' categories.
- Level of Education: The level of education is deemed quite influential on child labor involvement, with a significant lean towards 'Agree'.
- Area of Residence: Respondents overwhelmingly agree that the area of residence impacts the incidence of child labor, as evidenced by the high counts in 'Agree' and 'Strongly Agree'.
- Gender Influence: Opinions are more varied regarding gender's influence on child labor. While there are still more responses in the 'Agree' category than any other, there's a notable count in 'Strongly Disagree' and 'Neutral', indicating less consensus.
- Influence of Poverty: Poverty is perceived as having a very strong influence on child labor, with the majority of respondents placing this in the 'Agree' and 'Strongly Agree' categories.

Overall, it appears that socio-economic factors such as household income and poverty, as well as education levels, are considered to be significant influencers of child labor. Gender and age range are also seen as important but have a more varied consensus among the respondents.

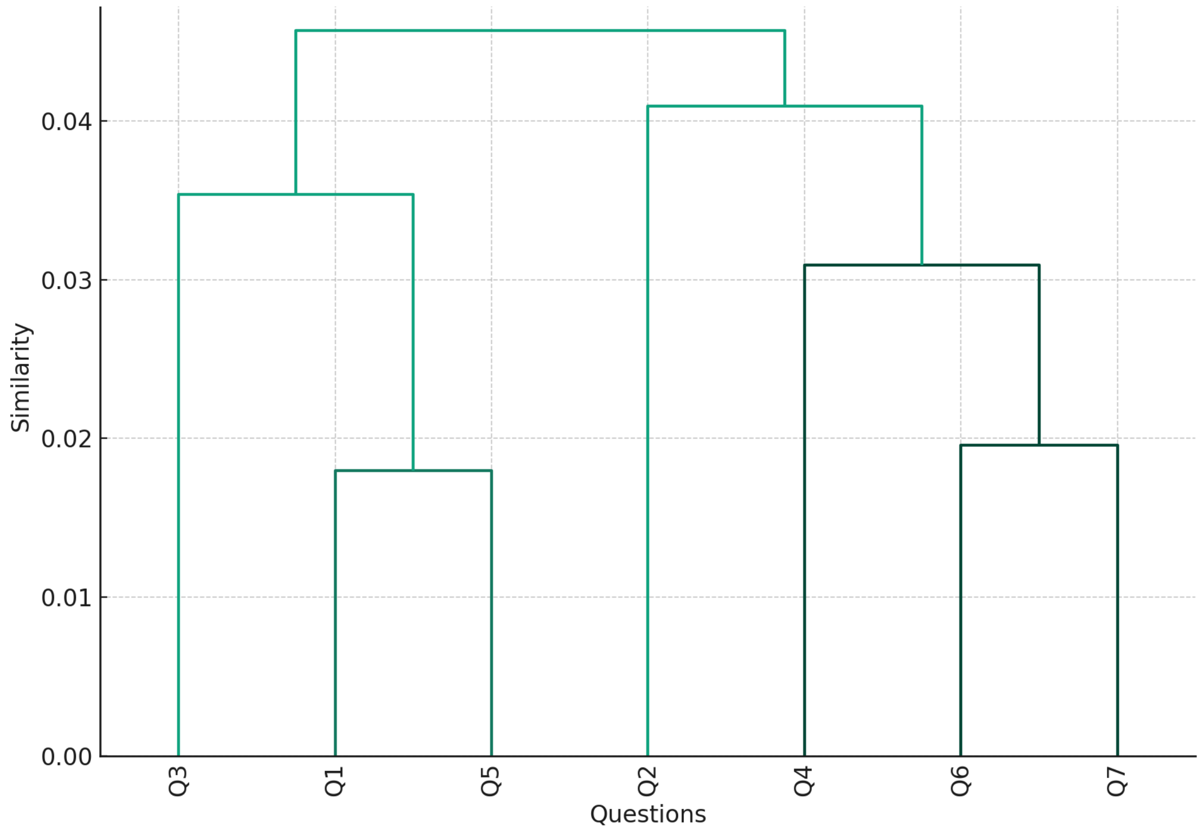

Figure 4. Dendrogram of Responses to Questions

Based on the dendrogram and the questions provided, here is an interpretation of the clustering:

Questions Q1 (age range's influence) and Q5 (area of residence's impact) seem to be the most similar in terms of responses. This suggests that respondents may perceive the influence of age and the area of residence on child labor as having similar levels of impact.

Questions Q2 (household income) and Q7 (poverty's influence) are clustered together at the highest level, indicating that the respondents see a strong relationship between household income and poverty when it comes to influencing child labor. This is intuitive, as these two factors are economically related.

Questions Q3 (type of work) and Q4 (level of education) are also grouped closely, suggesting that the nature of employment (formal vs. informal) and the level of education are perceived to similarly affect child labor.

Question Q6 (child's gender influence) stands alone and joins the other clusters at a higher threshold, which implies that the perceptions of gender influence on child labor are distinct from the other factors.

From these clustering, the dendrogram indicates that economic factors (household income and poverty) are viewed as closely linked in the context of child labor. Similarly, factors related to the work environment and education are also related. Meanwhile, gender stands out as a factor with a different pattern of influence according to the survey responses. This kind of analysis can be instrumental in targeting specific areas for intervention by identifying which factors are considered similar in their influence on child labor.

5. Conclusion

This paper underscores the critical importance of integrating logistic regression with the analysis of neutrosophic linguistic scales and similarity assessments. By examining the interrelationships between various socio-economic factors influencing child labor through this multifaceted approach, we achieve a more nuanced understanding that transcends traditional binary logistic regression models. The use of neutrosophic scales allows for capturing the uncertainty and indeterminacy inherent in human responses, while similarity assessments enable us to identify patterns and clusters in the data that might otherwise be overlooked. This integration facilitates a deeper exploration into the complex dynamics at play, offering a more robust and comprehensive framework for understanding the subtleties of human opinion and its impact on child labor.
For future work, the paper suggests expanding the current model to include a broader set of variables and a larger dataset, potentially drawn from diverse geographical regions to validate the universality of the findings. Additionally, the development of advanced computational tools to automate the neutrosophic analysis could significantly streamline the process, making it more accessible for larger-scale studies. Further research could also explore the application of this integrated approach to other social issues, examining whether the improved insights provided by the combination of logistic regression and neutrosophic linguistic scales hold consistent across different domains. Such studies could provide invaluable information for policymakers and social scientists working towards the mitigation of complex social problems.

6. References

[1]. UNICEF. Trabajo infantil: se elevan a 160 millones al alza por primera vez en dos decenios. Available online: https://www.unicef.org/es/comunicados-prensa/trabajo-infantil-elevan-160-millones-al-alza-primera-vez-dos-decenios (accessed on 20 January 2024).
[2]. BUREAU OF INTERNATIONAL LABOR AFFAIRS (ILAB, B.O.). Child Labor and Forced Labor Reports: Ecuador. Available online: https://www.dol.gov/agencies/ilab/resources/reports/child-labor/ecuador (accessed on 2 February 2024)
[3]. Basu, K.; Genicot, G.; Stiglitz, J. Household labor supply, unemployment, and minimum wage legislation. Policy and Research Working Papers 1999. Available online: https://ssrn.com/abstract=620651 (accessed on 13 January 2024).
[4]. Edmonds, E. Child Labor. Handbook of Development Economics 2007, 4, 3607–3709
[5]. Edmonds, E.; Schady, N. Poverty Alleviation and Child Labor. Economic Policy 2012, 4(4), 100-124. Available online: https://doi.org/10.1257/pol.4.4.100 (accessed on 6 January 2024).
[6]. Jara, H. X.; Montesdeoca, L.; Tasseva, I. The role of automatic stabilizers and emergency tax–benefit policies during the COVID-19 pandemic: Evidence from Ecuador. The European Journal of Development Research 2022, 34(6), 2787-2809. Available online: https://doi.org/10.1057/s41287-021-00490-1 (accessed on 2 April 2024).
[7]. Ministerio de Inclusión Económica y Social (MIES). (2023). Available online: https://www.inclusion.gob.ec/que-tipos-de-bonos-y-pensiones-entrega-el-mies/?preview=true (accessed on 2 April 2024).
[8]. Cecchini, S.; Atuesta, B. Programas de transferencias condicionadas en América Latina y el Caribe: Tendencias de cobertura e inversión. Santiago: Naciones Unidas, 2017. Available online: https://repositorio.cepal.org/handle/11362/41811 (accessed on 2 April 2024)
[9]. Edmonds, E.; Schady, N. Poverty Alleviation and Child Labor. Economic Policy 2012, 4(4), 100-124.
[10]. Basu, K.; Tzannatos, Z. The Global Child Labor Problem: What Do We Know and What Do We Do? World Bank Economic Review 2003, 17(2), 147-173.
[11]. Sikandar; Panezai, S.; Saqib, S.; Muhammad, S.; Bilal; Khan, I. Factors Determining Child Labor: Empirical Evidence from Khyber Pakhtunkhwa, Pakistan. Changing Societies & Personalities 2022, 6(1), 123–143.
[12]. INEC, Instituto Nacional de Estadística y Censos. (2022). Boletín Técnico - ENEMDU. Available online: https://www.ecuadorencifras.gob.ec/sistema-estadisticas-laborales-empresariales/ (accessed on 16 January 2024).
[13]. Rahman, M. A. Household characteristics and poverty: A logistic regression analysis. The Journal of Developing Areas 2013, pages 303-317.
[14]. Kandasamy, I.; Kandasamy, W. V.; Obbineni, J. M.; Smarandache, F. Indeterminate Likert scale: feedback based on neutrosophy, its distance measures and clustering algorithm. Soft Computing 2020, 24, 7459-7468.
[15]. Broumi, S.; Smarandache, F. Several Similarity Measures of Neutrosophic Sets. Neutrosophic Sets & Systems 2013, (1).
[16]. Das, A. Logistic regression. In Encyclopedia of Quality of Life and Well-Being Research; Springer International Publishing: Cham, 2021; pp. 1-2.

[17]. Lohmann, A.; Groenwold, R.H.; van Smeden, M. Comparison of likelihood penalization and variance decomposition approaches for clinical prediction models: A simulation study. Biometrical J. 2024, 66(1), 2200108.
[18]. Vásquez-Ramírez, M.R.; Moscoso-Paucarchuco, K.M.; Beraún-Espíritu, M.M.; Yupanqui-Villanueva, H.R.; Vivanco-Nuñez, O.A.; Yupanqui-Villanueva, W.F.; Gutiérrez-Gómez, E. Determination of the degree of relationship between Activity Cost and Financial Management in beef cattle production in a region of Peru, based on Indeterminate Likert Scale and Neutrosophic Similarity. Neutrosophic Sets Syst. 2024, 64, 84-90.
[19]. Kandasamy, I., and Smarandache, F. (2016) Triple refined indeterminate neutrosophic sets for personality classification. Paper presented at the 2016 IEEE Symposium Series on Computational Intelligence (SSCI).
[20]. Smarandache, F. n-Valued Refined Neutrosophic Logic and Its Applications to Physics. Prog. Phys. 2013, 4, 143.
[21]. Leonor, M. M., Easud, G. S., and Fernando, P. P. (2022) Indeterminate Likert Scale in Social Sciences Research. International Journal of Neutrosophic Science, 19, 289-297.
[22]. Chatterjee, R., Majumdar, P. and Samanta, S. K. (2019). Similarity Measures in Neutrosophic Sets-I in Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets, Switzerland, Springer Nature, pp. 249-294.
[23]. Chatterjee, R., Majumdar, P. and Samanta, S. K. (2019). Similarity Measures in Neutrosophic Sets-II in Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets, Switzerland, Springer Nature, pp. 295-326.
[24]. Banco Central del Ecuador. Reporte de pobreza, ingreso y desigualdad. Available online: https://contenido.bce.fin.ec/documentos/Estadisticas/SectorReal/Previsiones/IndCoyuntura/Empleo/indice_pobreza.htm (accessed on 18 January 2024).

Received: Jan 8, 2024. Accepted: Mar 29, 2024