Mathematical Modeling of the Number of Child Labor in the Philippines

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ABSTRACT

Mathematical modeling is the process of using mathematics to represent, analyze and solve real-world problems. This study aimed to analyze the trend of child labor cases in the Philippines from 2006 to 2015 and develop a predictive model to forecast the number of child labor cases for 2016 to 2018. The study adopted a descriptive-predictive research design, using publicly available data from the Philippine Statistics Authority (PSA). Nine mathematical models, including linear, quadratic, cubic, quartic, quintic, sextic, power, logarithmic, and exponential, were tested to identify the best fit for predicting child labor trends. Based on the statistical metrics of R-squared and standard error, the quintic model provided the best fit. The findings showed a decreasing trend in child labor cases during the study period, with predictions suggesting further reductions in future cases. The sextic model forecasted a value of 60%, 37% and -16% for child labor cases by 2016, 2017 and 2018, respectively. The study recommends continued monitoring of these trends, refining predictive models as new data emerges, and promoting public awareness to support efforts in reducing child labor.

Keywords: predictive modeling, r-squared, standard error, trend analysis

INTRODUCTION

Child labor presents a significant and multilayered challenge with complex economic, social, cultural, and legal roots (ILO, 2020). Poverty at the household level often forces families to rely on children's income to meet basic needs, even if it means sacrificing their education and well-being (Bezu & Dercon, 2009). Furthermore, a lack of decent work opportunities for adults can push children into the labor force to supplement family income (ILO, 2017).

Socio-cultural factors exacerbate these economic pressures. Cultural norms that normalize or glorify child labor, or limited access to quality education, can create a cycle where children are viewed as a source of immediate income for families, hindering their long-term opportunities (Akter, 2011). Additionally, inadequate legal frameworks that fail to define child labor effectively or lack clear regulations on minimum age for work create loopholes and hinder enforcement efforts (ILO, 2016). Even with strong legislation, weak enforcement mechanisms due to limited resources, societal awareness, or corruption can allow child labor to persist (UNICEF, 2021).

The consequences of child labor are far-reaching, impacting both education and health outcomes. Children engaged in labor often lack access to education, hindering their future opportunities and perpetuating the cycle of poverty (ILO, 2020). Moreover, these children are frequently exposed to hazardous working conditions, leading to physical and psychological health problems such as injuries, chronic illnesses, and mental health issues like depression and anxiety (ILO, 2017).

Addressing child labor requires a multi-faceted approach. This involves promoting economic development and creating decent work opportunities for adults, investing in quality education and making it accessible for all children, and strengthening legal frameworks and enforcing existing regulations on child labor. Additionally, raising awareness about the harmful effects of child labor and promoting cultural change are crucial. Finally, providing support services and alternative income opportunities for families at risk of pushing children into the labor force is essential to break the cycle of child exploitation. Through comprehensive and coordinated efforts, a future where all children have the opportunity to thrive and reach their full potential can be created (UNICEF, 2021).

However, child labor remains to be a persistent and complex issue with detrimental consequences for individual and societal well-being, especially that of the children. Like many countries, the Philippines continues to face challenges in addressing this problem despite international and national efforts to address. Reported child abuse cases, which often accompany child labor, reached over 16,000 in 2021 (Philippine Statistics Authority, 2022). Hence, understanding the trends, and contributing factors associated with child labor is crucial for developing effective prevention and intervention strategies.

With this context, this study aims to analyze the trend of child labor cases in the Philippines from 2006 to 2015 and to develop a predictive model using various mathematical approaches, to forecast the number of child labor cases for the years 2016 to 2018. Specifically, it aimed to determine the trend of child labor cases in the Philippines from 2006 to 2015; explore and analyze different mathematical models namely linear, quadratic, cubic, quartic, quintic, sextic, power, logarithmic, and exponential, and and predict the 2016 to 2018 number of child labor cases in the Philippines based on the best-fit model identified from the analysis.

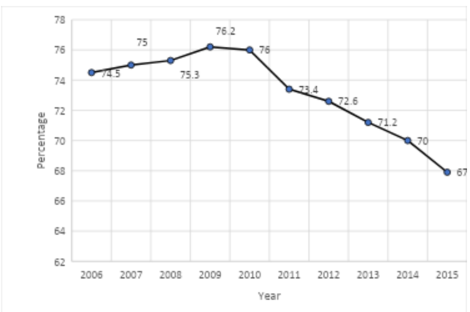
METHODOLOGY

This study adopted a descriptive-predictive research design. The data on reported child labor cases were downloaded from the official Philippine Statistics Authority (PSA) website. To explore and analyze different mathematical models, the data were preprocessed to ensure accuracy and then fitted to nine mathematical models: linear, quadratic, cubic, quartic, quintic, sextic, power, logarithmic, and exponential. Using software tools such as Excel, each model's coefficients were calculated through least squares regression techniques. The models were then evaluated based on statistical metrics such as R-squared and standard errors to determine which model provided the best fit. The best fit model was identified based on the model with the highest R-squared and lowest standard error. Once the best-fit model was identified, it was used to predict the number of child labor cases in the Philippines for the years 2016 to 2018. The model's equation was applied to extrapolate the data beyond 2015.

RESULTS AND DISCUSSION

Section 1. Trend of Child Labor in the Philippines

Figure 1
Trend of Child Labor in the Philippines

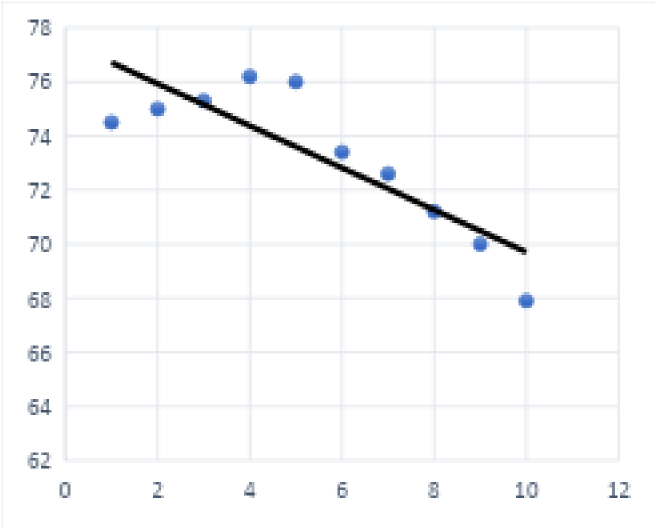


The general trend indicates a decrease in the percentage of child labor cases in the Philippines from 2006 to 2015. This decline highlights the progress made in addressing the issue, although continuous efforts are necessary to sustain and further this positive trend.

Section 2. Different Mathematical Models of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015.

Figure 2

Linear Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015



The negative slope of the linear model, −0.7776, indicates that for each passing year, the percentage of child labor cases decreases by approximately 0.7776%. This consistent decline suggests effective measures and interventions that may have been implemented over these years to combat child labor. The r-squared value of 0.7239 signifies that this linear model can explain approximately 72.39% of the variance in the percentage of child labor cases. This high r-square value implies a strong linear relationship between the year and the percentage of child labor cases, indicating that the model fits the data well. However, it is also essential to consider other potential mathematical models to capture different aspects of the trend. For instance, polynomial or logarithmic models could provide additional insights, particularly if there were periods of rapid change or plateauing that a simple linear model might not fully capture.

Figure 3

Quadratic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

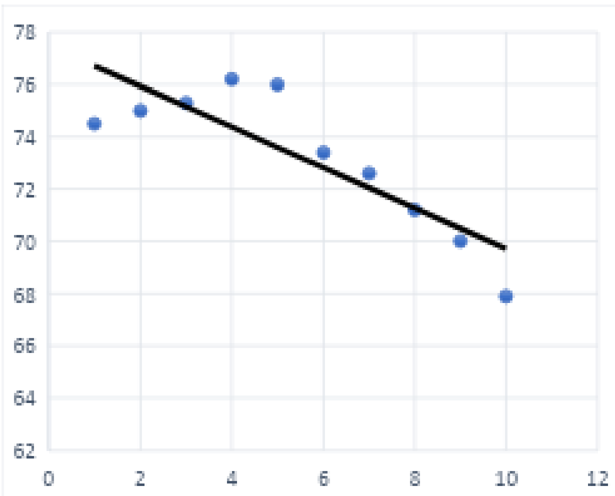


Figure 3 shows the quadratic model of the percentage of child labor in the Philippines from 2006 to 2015. The quadratic model is $y = -0.1746x^2 + 1.1433x + 73.645$ with r-squared of 0.9575. This indicates that the model can explain 95.75% of the variances. Compared with the linear model, the r-squared of the quadratic model is higher. This suggests that the quadratic model captures the trend more accurately than the linear model. The quadratic equation implies that the relationship between the years and the percentage of child labor is not strictly linear but involves a curve. Specifically, the negative coefficient of the x^2 term (−0.1746) suggests a downward-facing parabola, indicating that the rate of decrease in child labor cases accelerated over the period. Comparing the quadratic and linear models highlights the importance of considering different mathematical approaches to understand trends comprehensively. The quadratic model's higher r-squared value suggests a more nuanced and accurate depiction of the changes in child labor cases in the Philippines from 2006 to 2015, offering valuable insights for future policy development and targeted interventions.

Figure 4

Cubic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

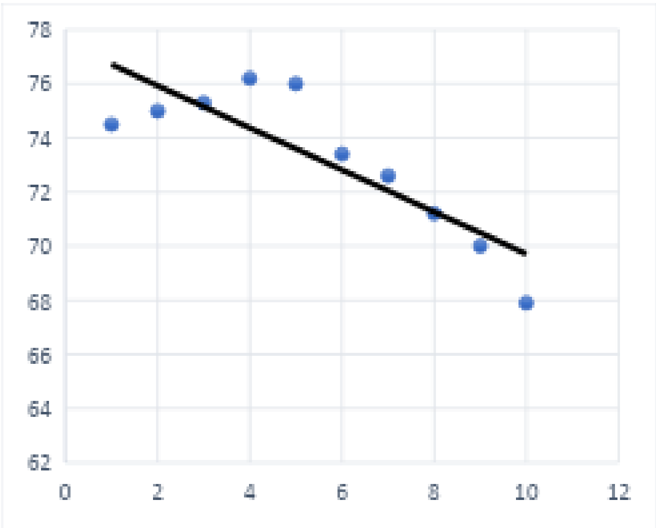


Figure 4 displays the cubic model of the percentage of child labor in the Philippines from 2006 to 2015. The cubic model is $y = 0.0154x^3 - 0.4281x^2 + 2.3125x + 72.327$ with r-squared of 0.9681. This shows that the model can explain 96.81% of the variances. It is also observed that the r-squared is higher than the quadratic model and linear model. The high R-squared value suggests that the cubic model provides an excellent fit to the data, capturing the underlying trend and fluctuations in child labor percentages over the specified period. This model's R-squared value is notably higher than the quadratic and linear models, indicating a superior ability to describe the data's variability. The coefficients of the cubic model indicate a complex, non-linear relationship between the years and the percentage of child labor. The positive cubic term ($0.0154x^3$) suggests that there may be an increasing rate of change in child labor percentages over time. The negative quadratic term ($-0.4281x^2$) and the positive linear term (2.3125x) further refine this relationship, highlighting periods of both increase and decrease within the overall trend.

Figure 5
Quartic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

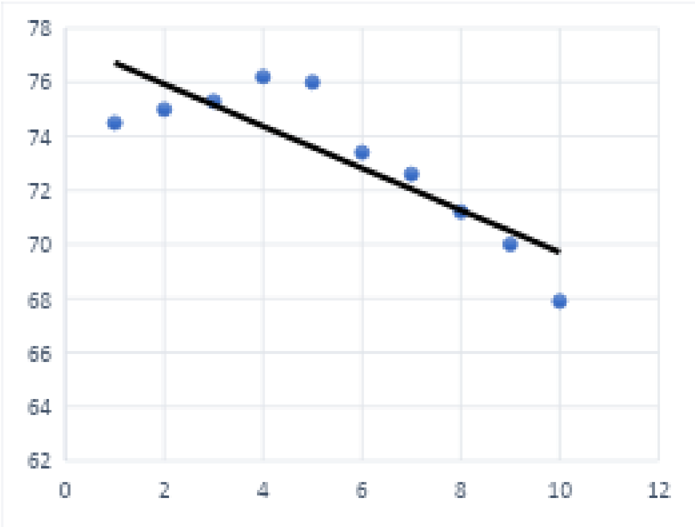


Figure 7 shows that the quadratic model is y = $0.0027x^4 - 0.0433x^3 + 0.0011x^2 + 1.1395x + 73.242$ with r-squared of 0.9698. This also reveals that the model can explain 96.98% of the variances. The r-squared of the quadratic model is slightly higher than the cubic model. The high R-squared value suggests that the quadratic model provides an excellent fit to the data, effectively capturing the overall trend in child labor percentages over the specified period. This model's R-squared value is slightly higher than that of the cubic model, indicating a marginally better ability to describe the variability in the data.

The coefficients of the quadratic model reflect a nuanced relationship between the years and the percentage of child labor. The positive fourth-degree term ($0.0027x^4$) suggests a complex pattern of change, while the negative third-degree term ($-0.0433x^3$) and the positive linear term ($1.1395x$) highlight periods of both increase and decrease within the overall trend. The small positive second-degree term ($0.0011x^2$) further refines this relationship.

Figure 6
Quintic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

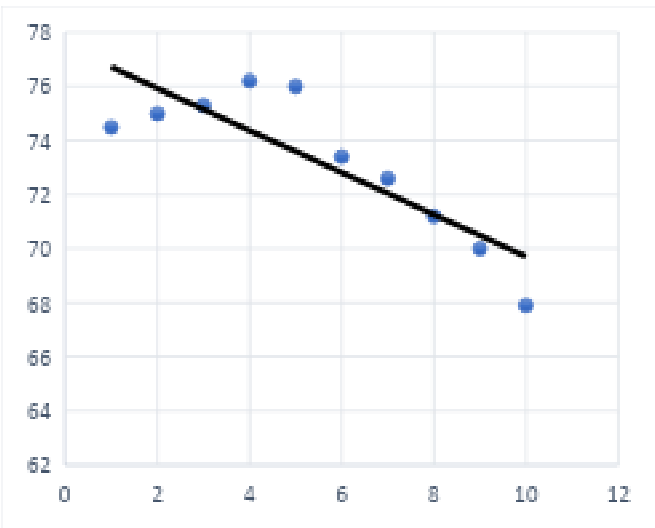
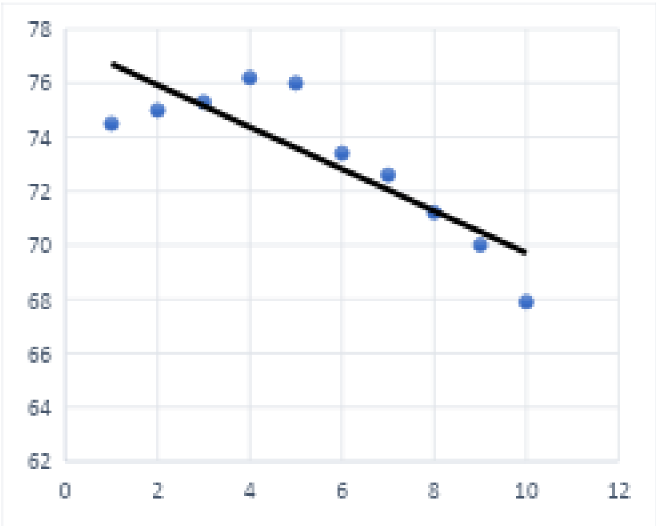


Figure 6 shows that the quintic model is y = $-0.0037x^5 + 0.1046x^4 - 1.0684x^3 + 4.5862x^2 - 7.5948x + 78.54$ with r-squared of 0.9853. It indicates that the model can explain 98.53% of the variances. The r-squared is higher than the quadratic model. The exceptionally high R-squared value suggests that the quintic model provides an excellent fit to the data, capturing the intricate and non-linear trends in child labor percentages over the specified period. This model's R-squared value is notably higher than the quadratic and cubic models, demonstrating its superior ability to account for the variability in the data.The coefficients of the quintic model reflect a highly complex relationship between the years and the percentage of child labor. The negative fifth-degree term ($-0.0037x^5$) and the positive fourth-degree term ($0.1046x^4$) indicate a pattern of fluctuations, while the negative third-degree term ($-1.0684x^3$) and the positive second-degree term ($4.5862x^2$) highlight periods of significant change. The negative linear term ($-7.5948x$-$7.5948x$–$7.5948x$) and the constant term (78.54) further refine this relationship, capturing the overall downward trend in child labor percentages over time.

Figure 7

Sextic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

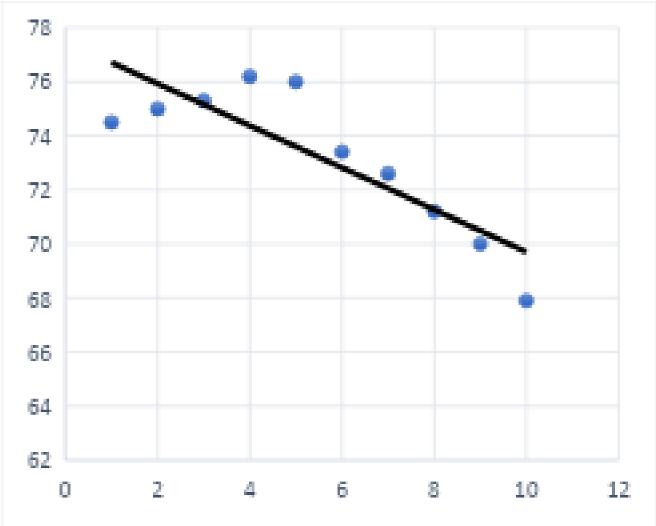


The figure displays the sextic model of the percentage of cases of child labor in the Philippines from 2006 to 2015. The model is $y = -0.0004x^6 + 0.0082x^5 - 0.0483x^4 - 0.1096x^3 + 1.5524x^2 - 3.1488x + 76.287$ with r-squared of 0.9859. It indicates that 98.59% of the variances can be explained by the model. This is the highest r-squared compared with linear to quintic. It can also be observed that the higher the degree of the polynomial equation, the higher the value of the r-squared. It also means that the equation fits the given data better. This R-squared value is the highest among the models tested, ranging from linear to quintic. The sextic model best fits the data, capturing the complexity and subtle variations in child labor percentages over the period. The trend observed here is that as the degree of the polynomial increases, the R-squared value also increases, implying that higher-degree polynomial equations tend to fit the data more closely. The coefficients of the sextic model indicate a highly complex and nuanced relationship between the years and the percentage of child labor. The negative sixth-degree term ($-0.0004x^6$) and the positive fifth-degree term ($0.0082x^5$) suggest alternating periods of increase and decrease. The negative fourth-degree term ($-0.0483x^4$) and the negative third-degree term ($-0.1096x^3$) highlight the intricate fluctuations within the overall trend. The positive second-degree term ($1.5524x^2$) and the negative linear term ($-3.1488x$) further refine this relationship, capturing the short-term and long-term variations in child labor percentages. Other than polynomial functions, other functions are also explored, such as power, logarithmic, and exponential functions.

Figure 8 shows that the power function is $y = 77.108x^{-0.035}$ with r-squared of .4312. This indicates that 43.12% of the variances can be explained by the model. Compared with the polynomial functions, the r-squared of power function is lower than any of the polynomial functions.

Figure 8

Power Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015



Compared to the polynomial models, the R-squared value of the power model is lower. This suggests that the power model does not fit the data and the polynomial models, which have R-squared values ranging from around 0.9681 to 0.9859. The lower R-squared value indicates that the power model is less effective in capturing the variations and trends in child labor percentages over the specified period. Despite its lower explanatory power, the power model can still provide some insights into the overall trend of child labor percentages over the years. It suggests a general, though weak, downward trend in child labor percentages. However, due to its limited ability to explain the variance, it may not be suitable for making precise predictions or for detailed analysis of the factors influencing child labor trends. Compared to the polynomial models, the power model's simplicity may be both a strength and a limitation. While it offers a straightforward representation of the data, it fails to capture the complexities and nuances that the higher-degree polynomial models can. This underscores the importance of selecting the appropriate model based on the specific requirements of the analysis. For policymakers and researchers, relying solely on the power model may lead to oversimplified conclusions and ineffective intervention strategies. Therefore, it is crucial to consider more complex models, such as the polynomial ones, for a more accurate and comprehensive understanding of child labor trends in the Philippines from 2006 to 2015.

As shown in Figure 9, the logarithmic model is $y = -2.509\ln(x) + 77$ with r-squared of 0.4418. This indicates that 44.18% of the variances can be explained by the model. The r-squared compared to the power model, which has an R-squared value of 0.4312, the logarithmic model performs slightly better in explaining the variance in the data. However, similar to the power model, the logarithmic model's R-squared value is significantly lower than those of the polynomial models, which range from around 0.9681 to 0.9859. This indicates that the logarithmic model is less effective in capturing the variations and trends in child labor percentages over the specified period. The logarithmic model's equation suggests a decreasing trend in child labor percentages over time, as indicated by the negative coefficient of the logarithmic term.

Figure 9

Logarithmic Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015

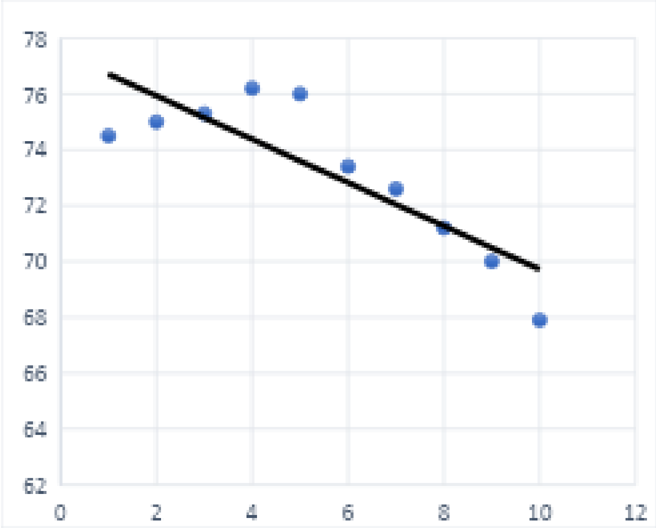
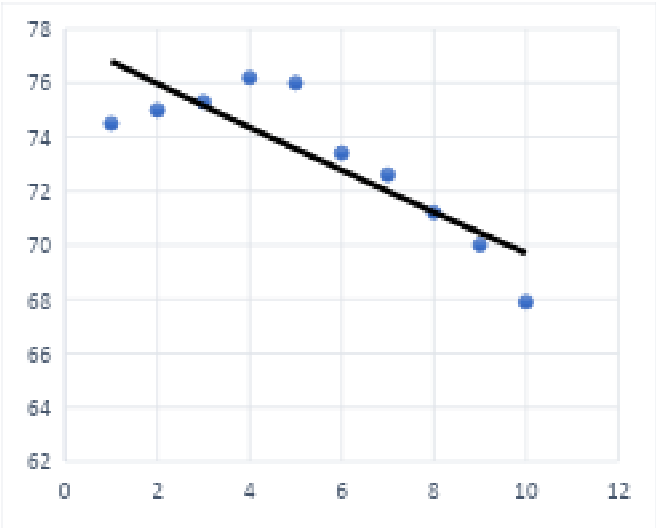


Figure 10

Exponential Model of the Percentage of Child Labor Cases in the Philippines From 2006 to 2015



As displayed in the figure, the exponential model is $y = 77.629e^{-0.011x}$ with R-squared of 0.7126. This means that 71.26% of the variances can be explained by the model. This model is higher than the power and logarithmic functions. Compared to the power and logarithmic models, which have R-squared values of 0.4312 and 0.4418 respectively, the exponential model demonstrates a significantly better fit to the data. This suggests that the exponential model is more effective in capturing the overall trend and variations in child labor percentages over the specified period. The higher R-squared value of the exponential model compared to the power and logarithmic models highlights its superior ability to explain the variance in the data. However, it is still lower than the R-squared values of the polynomial models, which range from around 0.9681 to 0.9859. This indicates that while the exponential model provides a relatively good fit, it may not capture all the complexities and fluctuations present in the data as effectively as the higher-degree polynomial models. The summary of the models, equations and R-squared is presented in Table 1.

Table 1

Summary of the Models, Equations and R-squared

Model	Equation	R-squared
Linear	$y = -0.7776x + 77.487$	0.7239
Quadratic	$y = -0.1746x^2 + 1.1433x + 73.645$	0.9575
Cubic	$y = 0.0154x^3 - 0.4281x^2 + 2.3125x + 72.327$	0.9681
Quartic	$y = 0.0027x^4 - 0.0433x^3 + 0.0011x^2 + 1.1395x + 73.242$	0.9698
Quintic	$y = -0.0037x^5 + 0.1046x^4 - 1.0684x^3 + 4.5862x^2 - 7.5948x + 78.54$	0.9853
Sextic	$y = -0.0004x^6 + 0.0082x^5 - 0.0483x^4 - 0.1096x^3 + 1.5524x^2 - 3.1488x + 76.287$	0.9859
Power	$y = 77.108x^{-0.035}$	0.4312
Logarithmic	$y = -2.509\ln(x) + 77$	0.4418
Exponential	$y = 77.629e^{-0.011x}$	0.7126

It can be gleaned from Table 1 that the lowest R-squared is 0.4312, and the highest is a sextic model, which is 0.9859. The analysis indicates that higher-degree polynomial models, particularly the quintic model, provide the best fit for the data on child labor percentages in the Philippines from 2006 to 2015. These models capture complex trends and variations more effectively than simpler models like the power, logarithmic, and exponential models. With its highest R-squared value, the quintic model is the most reliable for understanding and predicting changes in child labor percentages, making it a valuable tool for policymakers and researchers in formulating targeted interventions and policies. However, the standard error needs to be computed to verify this.

Section 3. Prediction of the Future Percentage of Child Labor Cases Using the Best-Fit Model

Table 2

Equation of the Models, R-squared, and the Computed Standard Error

Model	Equation	R-squared	Standard Error of Estimate
Linear	$y = -0.7776x + 77.487$	0.7239	1.54
Quadratic	$y = -0.1746x^2 + 1.1433x + 73.645$	0.9575	0.60
Cubic	$y = 0.0154x^3 - 0.4281x^2 + 2.3125x + 72.327$	0.9681	0.52
Quartic	$y = 0.0027x^4 - 0.0433x^3 + 0.0011x^2 + 1.1395x + 73.242$	0.9698	0.51
Quintic	$y = -0.0037x^5 + 0.1046x^4 - 1.0684x^3 + 4.5862x^2 - 7.5948x + 78.54$	0.9853	0.36
Sextic	$y = -0.0004x^6 + 0.0082x^5 - 0.0483x^4 - 0.1096x^3 + 1.5524x^2 - 3.1488x + 76.287$	0.9859	0.35
Power	$y = 77.108x^{-0.035}$	0.4312	2.21
Logarithmic	$y = -2.509\ln(x) + 77$	0.4418	2.19
Exponential	$y = 77.629e^{-0.011x}$	0.7126	1.57

As shown in Table 2, the highest R-squared is 0.9859. This confirms that the sextic model is the best-fit model among the different models.

Table 3

Actual Number of Child Labor Cases and the Predicted Numbers Using the Mathematical Models

Year		Percentage	Linear	Quadratic	Cubic	Quartic	Quintic	Sextic	Power	Logarithmic	Exponential
2006	1	74.5	77	75	74	74	75	75	77	77	77
2007	2	75	76	75	75	75	75	75	75	76	76
2008	3	75.3	75	76	76	76	76	76	74	76	75
2009	4	76.2	74	75	76	76	76	76	73	75	74
2010	5	76	74	75	75	75	75	76	73	75	73
2011	6	73.4	73	74	74	74	74	74	72	75	73
2012	7	72.6	72	73	73	73	73	72	72	75	72
2013	8	71.2	71	72	71	71	71	71	72	75	71
2014	9	70	70	70	70	70	71	70	71	75	70
2015	10	67.9	70	68	68	68	69	68	71	74	70
2016	11		69	65	66	68	63	60	71	74	69
2017	12		68	62	65	68	50	37	71	74	68
2018	13		67	59	64	70	21	-16	70	74	67

Table 3 shows predictions for child labor cases based on different models, with the sextic model giving the best results. According to this model, the percentage of child labor cases is expected to decrease over the years—from 67.9% in the original data to 60% in 2016, 37% in 2017, and -16% in 2018. This suggests a steady drop in child labor cases over time, indicating that the problem may be improving. These results can help guide future efforts to reduce child labor further.

Conclusion

The trend of child labor cases in the Philippines from 2006 to 2015 is decreasing. The linear, quadratic, cubic, quartic, quintic, sextic, exponential, logarithmic, and power model of the child labor cases in the Philippines respectively are: $y = -0.7776x + 77.487$, $y = -0.1746x^2 + 1.1433x + 73.645$, $y = 0.0154x^3 - 0.4281x^2 + 2.3125x + 72.327$, $y = 0.0027x^4 - 0.0433x^3 + 0.0011x^2 + 1.1395x + 73.242$, $y = -0.0037x^5 + 0.1046x^4 - 1.0684x^3 + 4.5862x^2 - 7.5948x + 78.54$, $y = -0.0004x^6 + 0.0082x^5 - 0.0483x^4 - 0.1096x^3 + 1.5524x^2 - 3.1488x + 76.287$, $y = 77.108x^{-0.035}$, $y = -2.509\ln(x) + 77$ and $y = 77.629e^{-0.011x}$. The best-fit model is sextic. Based on the sextic model, the predicted value is 60% in 2016, 37% in 2017, and -16% in 2018.

Recommendations

Since child labor cases have been decreasing from 2006 to 2015, it is important to keep tracking these trends. The quintic model can be used to regularly check if the trend continues and make adjustments if needed. The model predicts that child labor could drop to 63%, so keeping an eye on this forecast is good. This model could be used to guide planning and decisions about where and how to focus efforts to reduce child labor. The predicted value of 63% can help set realistic goals. But as more data becomes available, the models should be revisited to ensure they still fit well. Using more complex models or additional factors in the future to improve predictions and strategies should also be considered. Alongside data-driven strategies, public awareness and education about child labor should be promoted. This can help prevent child labor and support the overall goal of reducing it further.

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