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HEALTH RISKS ASSESSMENT FROM CADMIUM AND LEAD EXPOSURE IN STREET CHILDREN USING THE MONTE CARLO SIMULATION METHOD

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ABSTRACT
Street children represent a highly vulnerable subgroup of the urban population because of their prolonged and unregulated exposure to environmental pollutants and heavy metals, such as cadmium and lead. This study aimed to evaluate the non-carcinogenic health risks posed by Cd and Pb exposure among street children using a probabilistic assessment of health risks. This study employed a cross-sectional observational design and This study uses the MCS method to estimate non-carcinogenic and carcinogenic health risks due to heavy metal exposure.The research subjects were 107 street children with 6 air sample inspection locations in Makassar city. The results of the Monte Carlo simulations demonstrated that both the average Hazard Quotient and Target Hazard Quotient for Cd and Pb significantly exceeded the acceptable safety threshold of > 1, indicating substantial health risks. Cd levels were significantly correlated with the age of street children, whereas Pb levels were not.. These findings highlight the need for urgent public health interventions, environmental regulations, and protective policies to mitigate toxic exposure among street children in urban environments in the long term.
Keywords: Cadmium; Lead; Street Children; Probabilistic Risk Assessment; Monte Carlo Simulation**.**

I. INTRODUCTION

Heavy metals such as lead (Pb) and cadmium (Cd) are environmental contaminants that pose significant health risks, especially to vulnerable populations such as children(1).This vulnerability is particularly evident among street children, who are often exposed to high levels of pollutants due to living conditions characterized by poor sanitation and proximity to heavy traffic zones in urban environments(2). Urban areas experience significant emissions of heavy metals from motor vehicle activity and fuel combustion, leading to alarming concentrations of these toxic metals in air, soil, and road dust (3)Pb exposure is particularly detrimental to children's brain development, resulting in cognitive impairment and negative changes in intelligence quotient (IQ), as well as impacting neurological function(4) children are more sensitive than adults to non-carcinogenic risks associated with environmental pollutants (5)

Cd is known for its nephrotoxic and carcinogenic properties, as well as its potential to impair growth and immune function in children (6)Enhanced data collection and risk assessments are crucial to better understand and manage the long-term health implications associated with chronic exposure in vulnerable demographics(7). children's exposure to heavy metals in street dust had a higher non-carcinogenic risk compared to adults, underscoring the importance of using probabilistic models to highlight this vulnerability effectively (8). MCS is effective in analyzing uncertainty and variability associated with exposure parameters, refining health impact estimates for at-risk populations such as street children(9). MCS have demonstrated how different input parameters can impact health risk estimates from heavy metal exposure(10). Additionally, sensitivity analysis in MCS can identify key parameters that significantly impact risk estimates, which can inform the development of targeted, evidence-based mitigation strategies(11)

The application of MCS in assessing health risks associated with environmental contamination, suggesting that it can yield a more comprehensive understanding of exposure risks and inform public health policy Emphasizing cancer risk assessment and non-carcinogenic health impacts is critical to protecting vulnerable populations(12). Therefore, integrating probabilistic assessments can address a critical gap in understanding the complex interactions of environmental variables that influence health outcomes among populations such as street children in urban settings such as Makassar.

Figure 1.Map of ambient air sampling locations

II. MATERIALS AND METHODS

*A. **Design Study***

This study employed a cross-sectional observational design and uses the MCS method to estimate non-carcinogenic and carcinogenic health risks due to heavy metal exposure. MCS was chosen because it can capture uncertainty and variability in data and provide more accurate probability-based results. Using the meta-analytic model equation method, the MCS functions to determine the possibility of hazards or risks that can affect the health of the population in an area. MCS is a simulation technique that uses random sampling to solve quantitative problems involving uncertainty or variability. This technique allows for a more in-depth analysis of potential risks . By applying this method, it is possible to evaluate the impact of uncertain variables and identify different possible outcomes, which is crucial in data-driven decision-making. To run an MCS effectively, it is highly recommended to use software or applications that can assist in the simulation process. These tools are needed to generate random variables and repeat the simulation process through multiple iterations. In this study, Oracle Crystal Ball software version 11.1.2 was used as an add-in in Microsoft Excel 2018, which allows for automatic statistical and probability calculations.

*B. **Sampling Technique***

Environmental sampling was conducted in densely populated areas in Makassar City, with ambient air measurements 20 meters from the emission source. The location points were determined based on secondary data from the Makassar Police Traffic Unit, taking into account meteorological factors (wind direction and speed), land use, and traffic density levels. A total of six sampling points were selected in five sub-districts, namely Sudiang, Daya, Antang, Panaikang, Sudirman, and Cendrawasih. 107 subject samples were street children who were active in densely populated areas with inclusion criteria: under 18 years of age and routinely on the street for work, activities, or living for at least the last five years and exclusion criteria were Children with mental development disorders and children who were unwilling to participate were excluded from this study.

*C. **Data Analysis***

MCS is a quantitative technique for risk evaluation and analysis that relies on random values and The data used in this study consisted of the concentrations of heavy metals Cd and Pb measured through biological samples blood of street children, using the Atomic Absorption Spectrophotometry (AAS) method. In addition, demographic data such as age, gender, weight, length of stay on the street, and daily activities were also collected through a structured questionnaire. Exposure factors were estimated based on environmental measurements (metal levels in air and dust) and oral intake estimates through street food consumption. Toxicological parameters, including Reference Dose (RfD) for Cd and Pb, were obtained from the US-EPA Integrated Risk Information System (IRIS) database. Non-carcinogenic health risks were calculated using the HQ and THQ approaches, which are a comparison between

Chronic Daily Intake (CDI) and RfD. CDI is calculated based on heavy metal concentration, inhalation rate or ingestion rate, exposure frequency, exposure duration, body weight, and average exposure time, by US-EPA guidelines. The basic formula used is

$$\mathbf{CDI} = \frac{\text{C x IR x EF x ED}}{\text{WB x AT}} \qquad \text{(equation 1)}$$

Information
CDI : Chronic Daily Intake (μg/m^3/d)
IR : Inhalation rate (μg/m^3)
fE : Frequency of Exposure (d/y)
Dt : Duration of Exposure (y)
C : Concentration (mg/Kg)
WB : Body Weight (Kg)

$$\mathbf{HQ} = \frac{CDI}{RfD} \qquad \text{(equation 2)}$$

Information:
HQ : Hazard quotient (μg/m^3/d)
RfD : Reference of Dose (μg/m^3/d)

$$\mathbf{THQ} = \frac{\text{fE x Dt x R x C}}{\text{RfD x WB x AT}}\, 10^{-3} \qquad \text{(equation 3)}$$

Information:
THQ : Target Hazard Quotient (μg/m^3/d)
fE : Frequency of Exposure (d/y)
Dt : Duration of Exposure (y)
R : Inhalation Rate (Kg/h)
C : Concentration (mg/Kg)
RfD : References of Dose (mg/Kg)
WB : Body Weight (Kg)
AT : Time Average (d/y)

To accommodate uncertainty in input parameters, a probabilistic simulation was performed using the Monte Carlo method with 10,000 iterations. In this simulation, the probability distributions used were lognormal for Cd and Pb concentrations, normal for body weight, triangular for inhalation rate and ingestion rate, and uniform for exposure duration. The simulation results provide the distribution of HQ and THQ for each metal and HQ_total (sum of HQ_Cd and HQ_Pb), THQ_total (sum of THQ_Cd and THQ_Pb), and the estimated probability of HQ_total exceeding the safe threshold value (HQ> 1, THQ> 1), which indicates an unacceptable health risk.Sensitivity analysis was conducted to identify the input parameters that contributed most to the variation in HQ results. The Ranked Pearson Correlation Coefficient (PCC) and Standardized Regression Coefficient (SRC) methods were used to evaluate sensitivity, with the results visualized in the form of tornado diagrams. Through this analysis, parameters such as heavy metal concentration, ingestion rate, and body weight were identified as dominant factors influencing risk. In addition, statistical tests were conducted to support the data analysis. The Shapiro-Wilk normality test was used to determine the distribution of the data, while comparisons between groups based on age category or length of stay on the street were conducted using the t-test or Mann-Whitney U test, depending on the normality results. The results of the analysis are presented with 95% confidence intervals, both for HQ, THQ values and Monte Carlo simulation results, to increase the reliability of the interpretation of the research results. Monte Carlo Simulation was selected for its ability to incorporate variability and uncertainty in exposure parameters(13), which is essential in risk assessment among vulnerable populations such as children. This method allows probabilistic estimation of Hazard Quotient (HQ) and Cancer Risk (CR), which is more informative than deterministic methods(14).

III.RESULTS AND DISCUSSION

TABLE 1: AVERAGE NON-CARCINOGENIC RISK HQ AND THQ

Parameter	HQ	THQ
Cd	9.30×10^{-2}	1.11×10^{3}
Pb	7.25×10^{1}	8.69×10^{5}

Based on the data in Table 1, it shows that the average HQvalue for the Cd parameter is 9.30×10^{-2} μg/m^3/d and the average THQ value is 1.11×10^{3} μg/m^3/d. Meanwhile, the average HQ value for the Pb parameter is 7.25×10^{1} μg/m^3/d, and the average THQ value is 8.69×10^{5} μg/m^3/d. The high HQ and THQ values of Pb parameters indicate the need for serious environmental health policy interventions, especially in vulnerable groups such as street children. It should be noted that high THQ values indicate the potential for heavy metal accumulation in the body over time, which can cause neurological, cognitive, and other systemic disorders . While Cd shows a relatively low HQ value, the high THQ value reflects that although the exposure is small, its accumulation is risky in the long term

TABLE 2. ANALYSIS OF THE RELATIONSHIP BETWEEN AGE AND CADMIUM (CD) AND LEAD (PB) LEVELS IN BLOOD BIOMONITORING OF STREET CHILDREN IN HIGH-TRAFFIC AREAS OF MAKASSAR CITY.

age		Lead in Blood	Cadmium in the blood
Dense Transportation Area	r value	-0,103	-0,460
	P value	0,432	0,000

Based on the data in tabel 2 indicate two types of relationships between the age of street children and the levels of heavy metals in their blood. there is a very weak negative correlation between age and blood Pb levels, with a correlation coefficient of -0.103 and a significance value of 0.432. This value suggests that although the relationship is negative, it is not statistically significant. therefore, no meaningful association can be concluded between the children's age and their blood Pb levels.In contrast, a stronger and statistically significant negative correlation was found between age and Cd levels, with a correlation coefficient of -0.460 and a p-value of 0.000. This indicates that as the street children get older, the Cd levels in their blood tend to decrease, and this relationship is statistically meaningful.Therefore, only Cd levels show a significant correlation with the age of street children, whereas Pb levels do not.

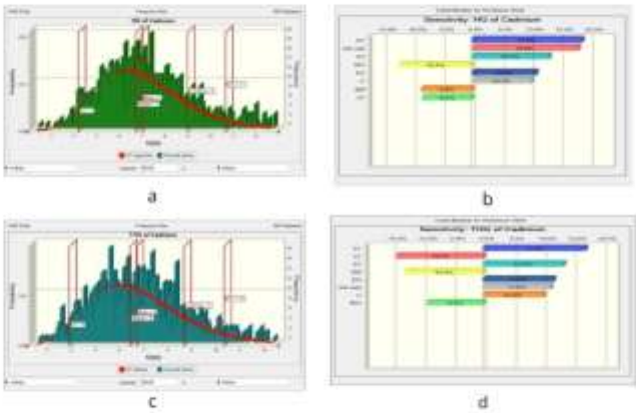

Figure 2.(a) Probabilistic of HQ Cd,(b)sensitivity of HQ Cd,(c)Probabilistic of THQ Cd, (d) sensitivity of THQ Cd

The probabilistic distribution of HQ for Cd exposure in children indicates a mean HQ of 1, exceeding the safe threshold set by the RfD (Figure.1a) Most simulated values are above HQ > 1, with a 5th percentile of 4 and a 95th percentile of 11, suggesting that nearly all children are at elevated non-carcinogenic health risk. This log-normal distribution reflects high variability influenced by Cd concentration, EF, and individual characteristics such as body weight. Sensitivity analysis reveals(figure 1b) that EF is the dominant factor, followed by inhalation rate 18.0%, ET per day 13.1%, and ED 10.9%. In contrast, RfC, BW, and AT show negative contributions of -12.4%, -8.6%, and -8.4%, respectively, indicating their mitigating role in reducing risk by lowering the Cd dose per body weight. Monte Carlo-based non-carcinogenic risk analysis provides a more accurate quantitative approach to understanding the potential health impacts of exposure to heavy metals such as Cd and Pb in children. In this study, the mean HQ values for Cd and Pb were found to be far above the safe threshold limit RfD, indicating that the potential health risk to the exposed population is very high. The probabilistic distribution of HQ Cd shows that most of the simulated values are above HQ > 1, with the 5th percentile being 4 and the 95th percentile being 11, meaning that 95% of the child population faces a real non-carcinogenic risk. This is in line with previous studies that emphasized that children, due to physiological and behavioral differences, are more susceptible to Cd exposure than adults(15). The log-normal distribution model generated in this simulation confirms the existence of significant exposure variability between individuals. Factors such as environmental concentration, inhalation pattern, and child weight are important elements that affect the magnitude of the internal dose of Cd.This uncertainty suggests that population-based risk assessments need to take into account individual heterogeneity to avoid risk estimation errors In the sensitivity analysis of HQ Cd, EF was shown to be the most influential factor, followed by inhalation rate and ET. This suggests that reducing the frequency of contact with pollutant sources can be an effective intervention in reducing risk levels (16).

The probabilistic distribution of THQ for Cd in children indicates an average value exceeding 1, suggesting potential non-carcinogenic health risks despite being within the RfC threshold(Figure 1c). Simulations show a 5th percentile of 4 and a 95th percentile of 10, meaning most of the population faces a very high risk. The log-normal distribution reflects significant variability influenced by Cd concentration, ED, and individual factors. Sensitivity análisis (Figure 1 d) identifies ET per day 17.0% as the most influential risk factor, followed by EF 13.3%, ED in years 11.6%, inhalation rate 11.2%, and Cd concentration 10.0%. Conversely, AT, BW, and RfC have mitigating effects of -14.5%, -13.0%, and -9.3%, respectively, as higher values in these parameters reduce Cd dose per body weight, thus lowering health risk. Interestingly, natural mitigation variables such as RfC, BW, and AT had negative contributions in the sensitivity analysis, meaning that increasing these factors correlated with decreasing health risks . Increasing body weight or RfC values, for example, leads to a decrease in the internal dose of Cd per unit body weight, thereby reducing the likelihood of toxic effects (17,18). The probabilistic distribution of the cadmium

THQ reinforces these findings, with the mean THQ value remaining above 1, indicating significant risk from chronic exposure. Most simulations for THQ Cd showed values between the 5th percentile of 4 and the 95th percentile of 10. This condition makes it clear that almost the entire simulated child population has a high potential risk due to Cd accumulation. This result is in line with the findings of (19), which highlighted that Cd exposure in children can trigger neurodevelopmental disorders and kidney function. In the sensitivity analysis of THQ Cd, ET was again the main factor, while AT, BW, and RfC showed negative contributions to THQ, emphasizing that these factors function as natural risk mitigators.

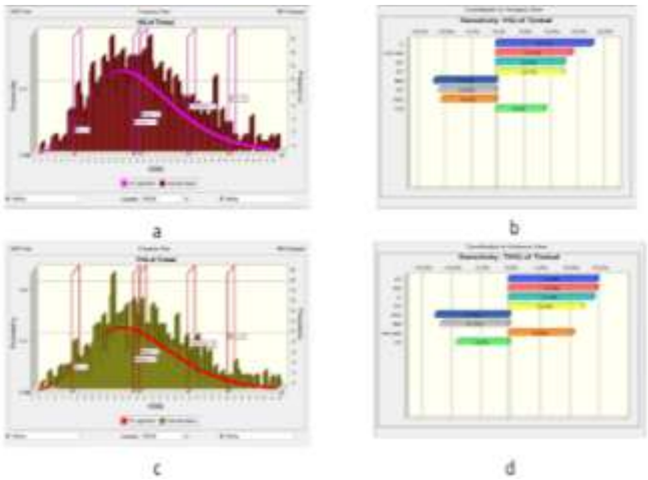

Figure 2. (a) Probabilistic of HQ Pb, (b) sensitivity of HQ Pb, (c) Probabilistic of THQ Pb,(d) sensitivity of THQ Pb

The probabilistic distribution of HQ for Pb exposure in children (figure.2 a)shows a mean HQ > 1, indicating potential non-carcinogenic health risks and exceeding the RfC threshold. With a 5th percentile of 1 and a 95th percentile of 4, 95% of the population falls within moderate to high-risk categories. The log-normal distribution reflects significant variability influenced by Pb concentration, exposure patterns, and body weight. Sensitivity analysis identifies Pb concentration(figure.2b) as the most influential factor 18.1%, followed by inhalation rate 14.3%, EF 12.8%, and daily ET 12.7%. Conversely, BW -11.7%, AT -10.8%, and RfC -10.4% contribute negatively, indicating their mitigating role in reducing Pb dose per body mass and thus lowering health risk. Exposure to Pb showed almost similar dynamics. The simulation results showed that the average HQ Pb exceeded the safe threshold with a distribution of the 5th percentile of 1 and the 95th percentile of 4. This indicates that most exposed children have non-carcinogenic health risks, both at moderate and high levels. The log-normal distribution for lead HQ reaffirms the importance of considering inter-individual variability in risk models. This variability shows that the assumption of homogeneity in the population is often unrealistic and can be misleading in risk mitigation planning (20). Sensitivity analysis of HQ Pb showed that the most dominant factor was the environmental Pb concentration, followed by inhalation rate and EF. This underscores the importance of controlling environmental Pb concentrations as a primary measure in protecting children's health. In addition, as with Cd, the variables BW, RfC, and AT showed negative contributions to HQ, indicating the existence of natural mitigation mechanisms through increasing the values of these factors (21).

The probabilistic distribution of THQ for Pb exposure in children reveals an average THQ > 1, surpassing the safe threshold based on the RfC (figur. 2c), indicating potential non-carcinogenic health risks under chronic exposure. With a 5th percentile of 1 and a 95th percentile of 4, 95% of the population is at high risk. The log-normal distribution reflects variability driven by Pb concentration, exposure patterns, and individual characteristics. Sensitivity analysis (figure.2 d)shows that ET and ED are the most influential factors, each at 14.9%, followed by Pb concentration 14.3%, EF 12.6%, and inhalation rate 10.8%. Mitigating factors include RfC -12.3%, BW -11.5%, and AT -8.8%, where higher values reduce the effective dose per body mass and consequently lower health risk. The probabilistic distribution for THQ Pb also showed a mean value above one, with the 5th and 95th percentiles being 1 and 4, respectively. This means that most of the simulated child population remains at high risk of experiencing non-carcinogenic health effects. (22)study also supports this finding, confirming that probabilistic methods tend to reveal greater actual risks than conventional deterministic methods. Sensitivity analysis of THQ Pb showed that ET and ED were the most positively influential factors, while the RfC, BW, and AT variables contributed negatively. These results suggest that efforts to reduce the duration and frequency of exposure can be an effective mitigation strategy. Conversely, paying attention to physiological factors such as increasing body weight through nutritional interventions can also contribute to risk reduction. In this context, the Monte Carlo-based approach provides advantages over deterministic methods because it can capture the uncertainty and variability of input data more accurately(23,24).

IV.CONCLUSIONS

Based on the results of the Monte Carlo-based probabilistic analysis of exposure to heavy metals Cd and Pb in children, it can be concluded that there is a very significant potential for non-carcinogenic health risks. The average HQ and THQ values for both metals show figures that consistently exceed the safe limits set by the RfC. The probabilistic distribution that follows a log-normal pattern confirms the existence of individual variability in exposure and response to heavy metals, with the majority of the population being in the high-risk category. Factors such as EF, inhalation rate, ET and ED, and pollutant concentration are the main determinants in increasing health risks. In contrast, the variables BW, AT, and RfC act as natural mitigation factors with negative contributions to risk. The results of the sensitivity analysis revealed that exposure reduction strategies can be directed by focusing on these critical factors. In addition, the Monte Carlo method is better able to capture uncertainty and variability than deterministic approaches, making it a very important tool in environmental health risk assessment, especially for vulnerable groups such as children. These findings reinforce the urgency of protecting public health from heavy metal exposure through strong evidence-based prevention efforts.

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