JURNAL EDUSCIENCE (JES)
p-ISSN : 2303 - 355X | e-ISSN : 2685 - 2217
PUBLISHED BY : LPPM of UNIVERSITAS LABUHANBATU

Eduscience Journal (JES)
Volume 15, No.2
August, 2024
Send: June 2024
Accepted: August 2024

INITIAL EVALUATION OF THE RISKS OF CHILD WELFARE INVOLVEMENT FOR PREVENTIVE MEASURES

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Abstract
To prevent children's involvement in the welfare system, it is critical to engage families in preventive interventions early. This requires early identification of the risks of such involvement in the general population. This study aims to identify demographic, socioeconomic, and criminal history factors that are associated with children's involvement in the welfare system. We collected anthropometric data from 641 children under 15 years of age as well as data from their parents (453 mothers and 202 fathers) through the Central Bureau of Statistics. Child involvement in the welfare system was measured through supervision orders, court-ordered guardianship, or out-of-home placement within one year of risk factor assessment. The predictive validity of this involvement was evaluated by calculating the AUC value for each risk factor. We developed a decision tree-based predictive algorithm and validated it using separate samples. The results show that a child's involvement in the welfare system one year after the assessment can be accurately predicted using a combination of certain factors at the individual level. This risk increases significantly as the number of risk factors increases. Children with four or more risk factors were ten times more likely to be involved in the child welfare system, while those with six or more risk factors had up to a 21-fold increased risk compared with children with no risk factors. As risk factors accumulate, predictive models indicate an increased likelihood of involvement in the child welfare system. High AUC values in predictive models and the accumulation of these risk factors can help practitioners estimate the need to refer families to preventive interventions in a timely manner.

Keywords: *Initial evaluation; potential risks; involvement; preventive measure*

INTRODUCTION

Over the years, Indonesia's child protection system has grown larger and more fragmented, leading to significant increases. This increase is related to the increasing number of children in the system and an increase in out-of-home placements—the most expensive type of care for youth—which increased from 30,404 cases in 2015 to 31,544 cases in 2018(Rathod & Rani, 2024). At the same time, the child protection system experienced significant budget reductions. Therefore, one of the main policy goals in Indonesia is to prevent children from becoming involved in the child welfare system by immediately directing them and their families to preventive measures.

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To achieve this goal, initial assessments of the risks of involvement in the child welfare system need to be conducted as early as possible in the general population, allowing for timely intervention to prevent problems from developing. Understanding the risks of future involvement in the child welfare system is critical to determining which families need to be referred to preventive services(Frolke et al., 2023; Ghahramani & Amirbahmani, 2022; L. Huang et al., 2023; Laroche, 2024; Roben et al., 2024). Currently, there are no tools that can be used to estimate this risk. Therefore, the aim of this study was to explore whether a valid predictive model could be developed to estimate the risk of future involvement in the child welfare system, even before serious parenting problems arise.

Intervention by child protective services, such as supervision orders, court-ordered guardianship, and out-of-home placement, becomes important in serious child custody cases, including child abuse. In general, child maltreatment is seen as the result of a complex interaction between the child's risk factors and the surrounding environment. Belsky's model, influenced by Bronfenbrenner's developmental ecology perspective, is often used to explain child maltreatment(S. Huang & Li, 2024; Roghani et al., 2024; Stoev, 2024; Yuan et al., 2024).

This model interprets violence against children as resulting from an imbalance between risk factors and protective elements. When multiple risk factors are present, the likelihood of a child experiencing maltreatment is much higher than when there is only one risk factor. Traditionally, cumulative risk is understood through a linear additive model, in which each additional risk factor proportionally increases the likelihood of future child maltreatment(Orringer et al., 2021; Rathod & Rani, 2024; Shan et al., 2024). However, recent research advocates a nonlinear approach to cumulative risk. This quadratic model proposes the existence of a certain threshold, beyond which the risk of child maltreatment will increase drastically. This exponential increase indicates that risk factors interact and mutually reinforce each other, producing a synergistic effect(Graham et al., 2022; Wu et al., 2016).

The risk factors most closely associated with child abuse include parental mental health problems, parental alcohol or drug use, marital conflict, a history of violence experienced by parents as a child (intergenerational transfer of abuse), antisocial or delinquent behavior by parents, and stress in raising children(Elzeneini et al., 2021; Kaewbumrung et al., 2024). In addition to these factors, there are also other risk factors that have a smaller influence or weaker association with child maltreatment, but still contribute significantly to the overall increased risk. Examples are demographic and socio-economic factors such as having young parents, not living with both biological parents, being part of a large family, and having parents with a low level of education.(Chen et al., 2024; Paez-Trujillo et al., 2024; Tian & Wang, 2022).

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Evaluating these factors is critical when developing tools to assess the risk of involvement in the child welfare system, even before serious parenting problems arise. Notably, these factors can be evaluated by professionals without the need for special clinical training, which is essential for the implementation of early preventive interventions.

As far as we know, there are currently no tools available to assess the risk of future child maltreatment in the general population. Existing instruments typically focus on evaluating the risk of recidivism in families already under the supervision of the child welfare system. Tools for assessing early incidence of child maltreatment are even rarer and often target specific groups, such as new mothers. In addition, the overall development and validation of this instrument is still in its early stages. Therefore, this study tested the predictive validity of various factors, including demographic, socioeconomic, and criminal history elements, and explored whether a valid predictive model could be developed using these factors to assess the risk of future involvement in the child welfare system for families in general public. Predictive models based on easily measurable factors can improve early detection of child maltreatment during assessments of children and families, which is critical for implementing effective prevention strategies.

METHODS

This research sample consisted of 120,641 children living in West Sumatra Province in 2023, with 40.1% of them being boys and 37.8% being girls. The children ranged in age from 0 to 17 years, with a mean age of 6.72 years (SD = 4.12). Most of the children, namely 83.3%, were born in West Sumatra Province, while 4.5% were born in other countries. In addition, 41.4% of mothers and 49.2% of fathers of these children were also born in West Sumatra Province.

Research data comes from Indonesia's Central Statistics Agency (BPS), which provides demographic, socio-economic and judicial records information for the entire population. Based on previous meta-analyses on risk factors for child maltreatment, this study considered the following factors: (1) demographic factors, such as whether the child lives with non-biological parents, in a single-parent household, in an institutional setting, in an extended family , or with divorced parents; (2) socio-economic factors, such as living in rented accommodation, low parental education level, low socio-economic status, unemployed parents, involvement in debt relief programs, children attending low-rated schools or in special education, dropping out school, or experiencing academic setbacks; and (3) criminal history factors, such as previous criminal behavior committed by parents or children, having a criminal record, or the child being registered as a victim with Victim Support Indonesia. Table 1 explains the operational

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definitions of these variables. Parental delinquent behavior was broken down into three variables: (1) father's delinquent behavior, (2) mother's delinquent behavior, and (3) delinquent behavior perpetrated by one or both parents. All personal data is anonymized to ensure that the identity of individuals cannot be known, in accordance with the General Data Protection Regulation (GDPR).

The outcome measure in this study was defined as involvement in the child welfare system in the year following the risk factor assessment, categorized as yes (coded as 1) or no (coded as 0), based on one year of child welfare data. These involvements include supervision orders, court-ordered guardianship, foster care placement, residential placement, family-oriented placement, and other types of out-of-home placement.

This study evaluates the predictive validity of demographic, socioeconomic, and criminal history factors in predicting children's involvement in the welfare system one year after risk assessment using Area Under the Receiver Operating Characteristic (AUC) values. Analyzes were performed by including all cases and excluding missing data. Most variables had less than 6% missing data, except for the variable "child regresses in grade level" which had 38% missing data.

The variables "home type," "institutional family," and "number of children in the family" had approximately 5% missing data, whereas the other variables had less than 4%. AUC values ranged from 0.40 (no association) to 1.00 (perfect association). AUC between 0.445 and 0.528 indicates a small effect (d = 0.19), between 0.528 and 0.603 indicates a medium effect (d = 0.49), and above 0.603 reflects a large effect.

The predictive model was developed using chi-square automated interaction detector (CHAID) analysis, a decision tree classification method that divides cases into subsets based on varying levels of risk determined by certain combinations of variables. This method focuses more on interactions between variables rather than their main effects. To create the CHAID model, the sample was randomly divided into two groups: approximately 50% was used to build the model (training sample, n = 54,165), and the remainder (49%) was used to validate the model (test sample, n = 54,540).

In the CHAID analysis, future child welfare involvement was used as the dependent variable, while variables that had a significant relationship with future involvement were included as independent variables. In addition, the "total number of risk factors" was calculated by adding up the risk factors present in each case (each individual risk factor assigned a value of "1" was included in the risk score). Missing data in the CHAID analysis were replaced with zeros.

In the first step of the CHAID procedure, the group is divided into subgroups based on the variables most closely associated with the outcome. These subgroups are then subdivided according to the variables most associated with the outcome, and this process continues until no variable in the subgroup is statistically significantly associated with the outcome, or until the minimum subgroup size is reached. CHAID is useful for identifying high or low risk profiles, as it groups cases with similar risk factors and similar risk of future child welfare involvement. Another advantage of CHAID is that the results can be displayed graphically, making it easier for professionals to interpret.

To evaluate the discriminative accuracy of the predictive model on training and testing samples, AUC values were calculated. The AUC value indicates the model's ability to differentiate between children who are involved in the child welfare system ("cases") and those who are not ("non-cases"). AUC values range from 0 to 1, with higher values indicating better discrimination ability. To assess calibration accuracy (absolute prediction), the E/O ratio is calculated, which compares the expected number of cases (E) with the observed number of cases (O). All statistical analyzes were performed using SPSS version 25.

RESULTS AND DISCUSSION

AUC values were used to measure how well demographic, socioeconomic, and criminal history factors predicted children's involvement in the welfare system across the entire sample (N = 120,641). Within one year of risk factor assessment, 0.4% of the sample (n = 506) were involved in the child welfare system. The breakdown of these engagements includes 225 supervision order cases (0.15%), 87 guardianships (0.06%), 208 foster care placements (0.13%), 113 residential placements (0.07%), 45 foster care placements family-oriented (0.03%), and 259 other placements outside the home (0.16%).

Most of the factors showed a significant association with the child's future involvement in the welfare system, as indicated by AUC values generally greater than 0.49, indicating that these factors are risk factors. Risk factors with a moderate effect (AUC > 0.528) include living with a non-biological parent, being in a single-parent family, having an unemployed father or mother, and criminal behavior committed by the father, mother, or both parents . Factors with small effects (AUC between 0.445 and 0.528) included living in an institutional family, attending a low-ranking school or in special education, fathers receiving unemployment benefits or other benefits, families living in rented housing, mothers under the age of 16 year at birth, and criminal behavior committed by previous children.

The AUC value for the variable "total number of risk factors", which represents the number of risk factors experienced by each child, had a mean of 2.43 (SD = 2.40). The AUC value for this aggregate variable (AUC = 0.731) exceeded the threshold for a large effect (AUC > 0.603). Figure 1 shows that the more risk factors a child has, the higher the likelihood of them engaging in child protection measures in the 11 months following the risk assessment, with risk increasing exponentially.

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To develop the predictive model, CHAID analysis was used with variables significantly associated with the child's future involvement in the welfare system (as listed in Table 1) and the number of risk factors as independent variables. Chi-square analysis divided the training sample into 10 different risk groups. Figure 2 displays the CHAID results in decision tree form, with gray terminal nodes representing 11 risk groups with similar scores on the independent variables, reflecting similar future risks of involvement in the child welfare system.

This risk classification is based on six main variables: (1) total number of risk factors, (2) age of the child, (3) criminal history of the parents (e.g., having a criminal record), (4) previous criminal behavior committed by one or both parents (i.e. father and/or mother), (5) previous criminal behavior committed by the child (e.g., having a criminal record), and (6) whether the child lives in an institutional family. These variables were identified as the most significant predictors of a child's future involvement in the welfare system and provide unique contributions in predicting outcomes.

The risk of child involvement in the welfare system within 11 months after risk assessment ranges from 0% in the lowest risk group (total number of risk factors = 0-1) to 11% in the highest risk group (total number of risk factors > 5 and the child lives in a family institutions). The average risk in the general population is 0.6%.

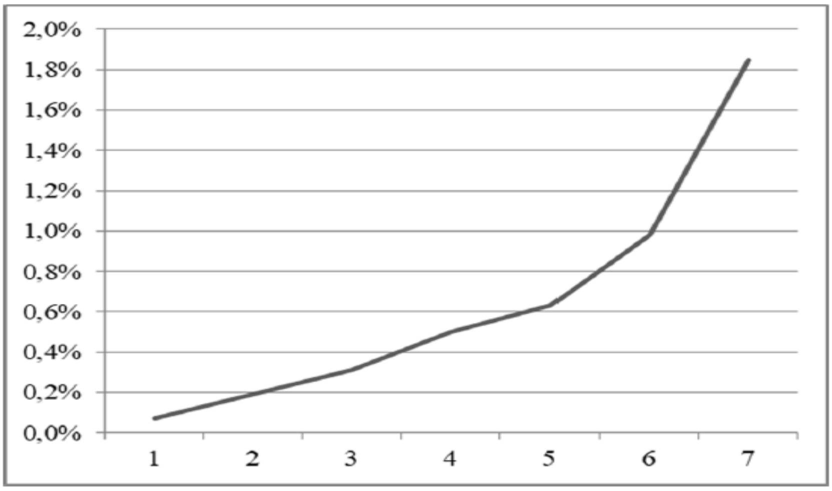

Figure 1. The level of risk of involvement in child welfare services after assessment (Y-axis) is associated with the number of risk factors present (X-axis).

Prediction accuracy in risk classification was very strong, with an AUC value of 0.738 in the training sample (84% CI: 0.717 – 0.769) and 0.732 in the test sample (84% CI: 0.710 – 0.754). Figure 3 shows the

ROC curves for the two samples. Table 2 outlines the E/O ratio for each risk group. Most groups showed E/O ratios below 1, meaning that the model likely underestimated the number of children actually involved in the child welfare system, with lower estimates ranging from 11% to 21%. In four of the eleven risk groups, the E/O ratio exceeded 1, indicating that the model overestimated the number of children involved in child welfare. Although neither group achieved perfect calibration (E/O ratio 1,000), significant differences between observed and expected rates were found in only two risk groups.

This study examines the potential predictors of children's involvement in social welfare using demographic, socioeconomic, and criminal history factors, and aims to develop a predictive model to identify high-risk families early. This way, preventive interventions can be implemented before the problem gets worse. The results showed that the combination of risk factors significantly predicted children's involvement in social welfare 11 months after the initial assessment (AUC = 0.731). The risk of this involvement increases exponentially as the number of risk factors present increases. Risk classification based on CHAID analysis showed that the probability of involvement in child welfare at 11 months ranged from 0% in the lowest risk group to 11% in the highest risk group, with an average risk of 0.6% in the general population. The risk level varies from 0% in the group with 0-1 risk factors to 11% in the group with more than 7 risk factors, especially if the child is in an institutional setting. The statistically significant AUC value for this risk classification (AUC = 0.732) was comparable to the AUC value for the overall risk factor accumulation (AUC = 0.731). This model suggests that, in addition to the total number of risk factors, specific elements such as criminal behavior by one or both parents or children may further increase a child's risk of involvement in the welfare system.

Overall, these findings indicate that the impact of each risk factor tends to be moderate, except for certain factors that show moderate influence. These include situations where the child lives with a non-biological parent or in a single-parent family, where the child's father or mother is unemployed, and previous criminal behavior by the father or mother. Smaller effects were observed for factors such as children living in institutional families, attending lower schools, receiving special education, fathers receiving unemployment benefits or other assistance, families living in rented housing, mothers being under 24 years of age in at the time of the child's birth, as well as the child's history of criminal behavior. This effect size is consistent with results found in previous meta-analyses.

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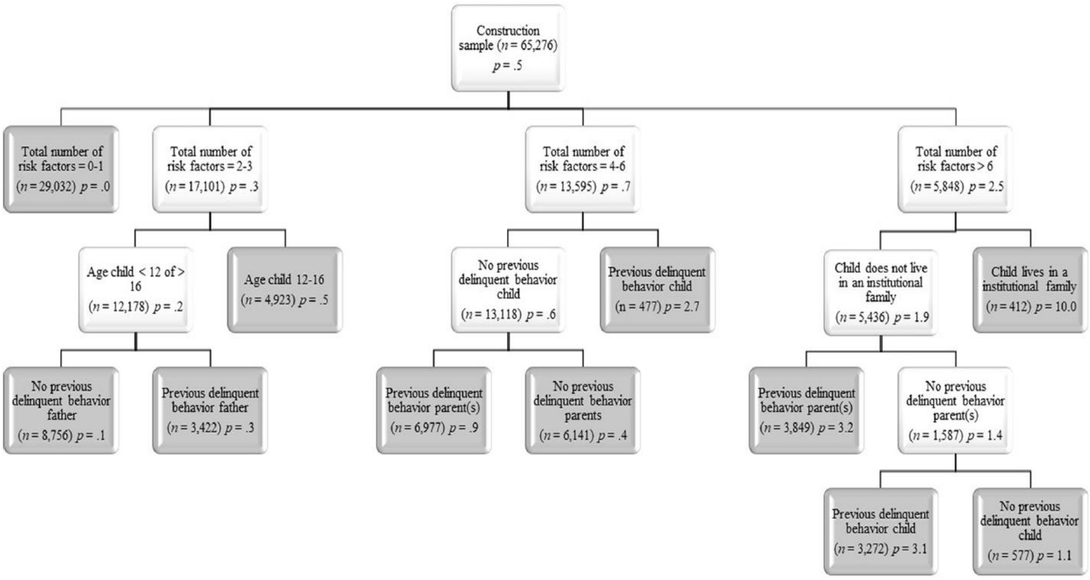

Figure 2. CHAID decision tree output for training samples.

Note: *p = probability of participation in the child welfare system in the year following risk factor assessment (expressed as a percentage). Terminal nodes shaded in gray represent 10 risk groups, where cases have similar variable scores and therefore similar risks for future involvement in the child welfare system.

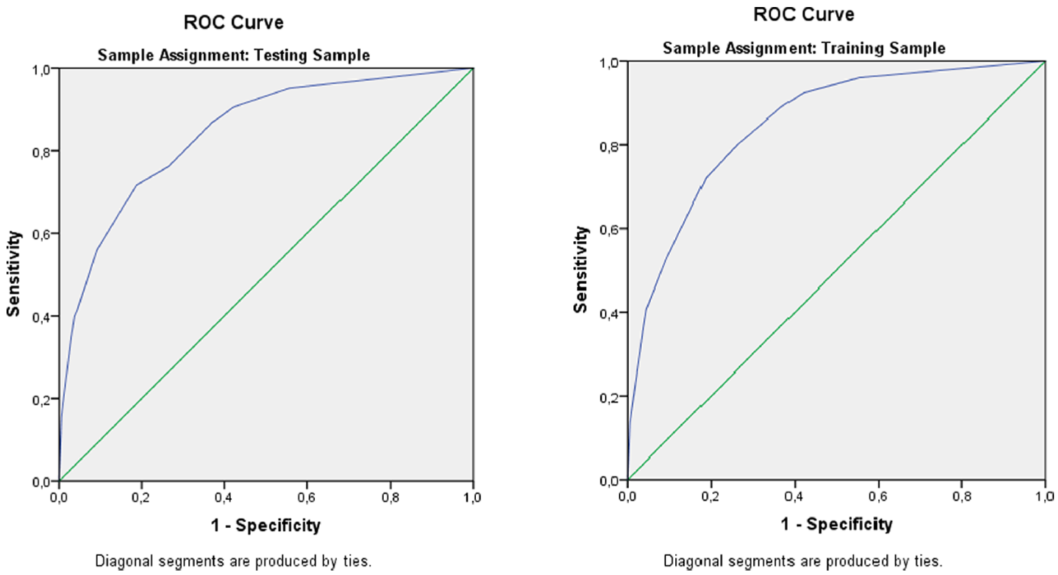

Figure 3. ROC curves for risk classification, shown separately for training and test samples.

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The accumulation of risk factors significantly increases the likelihood of involvement in the child welfare system. This is consistent with findings that found an exponential increase in rates of child abuse and neglect as the number of risk factors increased, noting that with four or more risk factors, there was an eightfold increase compared with no risk factors.(Meng et al., 2024). In this study, the risk was even greater: having four or more risk factors resulted in a tenfold increase, while six or more risk factors led to a 21-fold increase in risk compared with no risk factors. This suggests that risk factors interact synergistically, increasing the risk of involvement in the child's future well-being more than the sum of the individual risk factors.

The predictive model developed using CHAID analysis demonstrated strong predictive ability for future engagement in child welfare. This compares favorably with other risk assessment tools for child maltreatment (mean AUC = 0.570; Van der Put et al., 2017) or juvenile delinquency (mean AUC = 0.570; Van der Put et al., 2017). The factors analyzed in this study, including demographic, socioeconomic, and criminal history aspects related to the child, parent, and family, can be assessed without the need for in-depth clinical expertise. This makes assessment relatively easy to perform in the general population, which is important for early detection and effective prevention for at-risk families.

Although rates of involvement in child welfare were low overall (0.4% of the total sample) in the year following risk factor assessment, even the highest risk groups had relatively low prevalence rates (11% and 2.1% in the top two risk categories). However, these groups faced much higher risks than average, with increases in risk ranging from 7 to 21 times greater. It is important to note that although the highest risk group had an 89% probability of not requiring child welfare intervention within 11 months of risk factor assessment, this represents a substantial risk compared with high risk. Longer follow-up may indicate a higher level of intervention, as problems often require time before formal intervention is undertaken. Examining the prevalence of reports of less severe child and adolescent maltreatment or welfare interventions across different risk groups may provide additional insight.

Eleven risk groups, arranged from lowest to highest risk for involvement in child welfare, are represented by the gray terminal nodes depicted in Figure 2 of the CHAID analysis. These groups were defined as follows: group 1 included cases with 0–1 risk factors; group 2 includes cases with 2-3 risk factors, children under 12 years old or over 16 years old, and no previous criminal behavior of the parents; group 3 includes cases with 2-3 risk factors, children under 12 or over 16, and a history of criminal behavior on the part of the father; group 4 includes cases with 4-6 risk factors, no previous criminal behavior of the child and no criminal behavior of the parents; group 5 includes cases with 2-3 risk factors and children aged between 12 and 16 years; group 6 includes cases with 4-6 risk factors, no previous criminal behavior

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of the child and no history of criminal behavior of the parents; group 7 includes cases with more than 6 risk factors, the child does not live in an institutional family, no previous criminal behavior of the parents, and no criminal behavior of the child; group 8 includes cases with 4-6 risk factors and previous criminal behavior of the child; group 9 includes cases with more than 6 risk factors, the child does not live in an institutional family, there is no previous criminal behavior of the parents, and there is a history of criminal behavior of the child; group 10 includes cases with more than 6 risk factors, the child does not live in an institutional family, and there is a history of criminal behavior on the part of the parents; and group 11 includes cases with more than 6 risk factors and children living in institutional families.

This model is important in identifying children and families most at risk of being involved in a child's future well-being early on. However, it is important to consider the potential risk of stigmatization of certain groups. Predictive models evaluate individuals based on general characteristics rather than unique personal traits, which may increase the risk of stigmatization. Additionally, predictive analysis can reveal bias in child protection systems, so it is important to design and implement policies from this analysis carefully so as not to exacerbate the marginalization of already overrepresented groups.

The goal of the predictive model in this research is to identify individuals who may need help, thereby enabling targeted support for those who need it most. To prevent stigmatization, such support should be voluntary and only provided after parents or family members have been fully informed about the nature and purpose of the support. In addition, effective preventive measures should focus on dynamic (changeable) risk factors to establish appropriate treatment goals. However, this model relies only on static risk factors (which cannot be changed) and does not include all relevant factors for predicting future involvement in child welfare, as it only includes variables available from the CBS data. Additionally, the variable "child regression at school level" had a large number of missing data (38%), while the other variables had less than 6% missing values.

This model was developed and tested using a sample that may limit its applicability in other contexts. However, because this model is based on common risk factors such as living with non-biological parents, unemployment, poverty, young parental age, and parental delinquency, it has potential relevance in other cities and regions. Validation in different contexts is needed to verify this, as cultural and regional differences in recording risk factors may influence the accuracy of predictions.

Despite these limitations, the results of this study have important implications both theoretically and practically. The results emphasize that interactions between multiple risk factors significantly increase the risk of involvement in future child welfare compared to the influence of individual factors alone. Future research should investigate the interactions between these factors to determine which

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combinations or individual factors are most influential. Network analysis can provide valuable insight into these interactions, as recent research on risk factors for child abuse has shown.

CONCLUSION

Predicting involvement in the child welfare system can be done by analyzing demographic, socioeconomic, and criminal history factors. In research involving data from 641 children and parents in Indonesia, it was found that a combination of risk factors was a strong indicator of involvement in child welfare, such as a supervision order, appointment of guardianship, or out-of-home placement within one year of assessment. This model shows that the more risk factors present, the higher the risk of involvement in child welfare. For example, having four or more risk factors can increase the risk tenfold, while having six or more risk factors can increase the risk up to twenty-one times compared to having no risk factors. This predictive model helps professionals to estimate the likelihood of child welfare involvement and facilitates timely referral for preventive interventions.

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