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# Causal Modeling of Factors Causing Toddler Stunting Using the Peter-Clark Algorithm

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**Abstract**

Stunting is a growth disorder in toddlers that can result in a height that is not proportionate to their age. Between 2016 and 2024, many studies have discussed factors related to stunting. However, these studies generally only use correlation analysis, which indicates the level of closeness of the relationship between variables. Correlation analysis can indeed describe the existence of an association, but cannot explain the causal relationship. Therefore, the causal mechanisms underlying these factors have not been fully revealed. This study aims to model the causal relationship of the factors that cause stunting. This study uses the Peter-Clark algorithm to obtain the direction of the causal relationship. The results of this study show a relationship between Height(TB.U)/Weight(BB.U), Integrated Health Post Visits/Height(TB.U), Height(TB.U)/Mother's Education, Age of Marriage/Mother's Education, Immunization/Family Members Smoking in the Home, and Exclusive Breastfeeding/ Integrated Health Post Visits. The Peter-Clark algorithm in this study successfully identified a causal relationship based on a comparison of performance using directional and causal density of 67%. These results are quite informative, but 34% of the relationships remain undirected. Therefore, additional data, domain assumptions, or advanced algorithms, such as FCI or GES, are needed to determine their direction.

**Keywords**: *Causal; PC-Algorithm; Stunting; Toddler*

***Abstrak***

Stunting merupakan suatu kondisi gangguan pertumbuhan pada balita yang dapat mengakibatkan tinggi badan tidak sesuai dengan usianya. Dalam rentang 2016-2024 banyak penelitian yang membahas tentang faktor-faktor yang berhubungan dengan kejadian stunting. Namun, penelitian-penelitian tersebut umumnya hanya menggunakan analisis korelasi yang menunjukkan tingkat keeratan hubungan antarvariabel. Analisis korelasi memang dapat menggambarkan adanya asosiasi, tetapi tidak dapat menjelaskan hubungan kausalitas. Oleh karena itu, mekanisme kausal yang mendasari faktor-faktor tersebut belum sepenuhnya terungkap. Penelitian ini bertujuan untuk memodelkan hubungan kausal dari faktor-faktor kejadian stunting. Penelitian ini menggunakan algoritma Peter-Clark untuk mendapatkan arah hubungan kausal. Hasil penelitian ini menunjukan hubungan antar; TB.U dan BB.U, Kunjungan Posyandu dan TB.U, TB.U dan Pendidikan Ibu, Usia Ibu Menikah dan Pendidikan Ibu, Imunisasi dan Anggota Keluarga Merokok dalam Rumah, serta Asi Eklusif dan Kunjungan Posyandu. Algoritma Peter-Clark dalam penelitian ini berhasil mengidentifikasi hubungan kausal berdasarkan perbandingan kinerja menggunakan densitas terarah dan kasual sebesar 67%. Hasil tersebut cukup informatif, namun masih ada 34% hubungan yang tidak terarah. Sehingga, perlu data tambahan, asumsi domain, atau algoritma lanjutan, seperti FCI atau GES untuk menentukan arahnya.

***Kata-kata kunci****: Algoritma Peter-Clark; Balita; Kausal; Stunting*

## 1. Introduction

Stunting is a growth disorder in children under five years old, characterized by a height that is not proportionate to their age. The primary factor triggering stunting is chronic malnutrition, specifically a prolonged lack of nutritional intake [1]. According to the Regulation of the Minister of Health of the Republic of Indonesia Number 2 of 2020 concerning anthropometric standards for assessing children's nutritional status, stunting is determined based on the height-for-age (H/A) index with a value below -2 standard deviations (SD) [2]. Stunting is not only limited to physical growth disorders, but also makes toddlers more susceptible to disease, experiences obstacles in brain and intelligence development, and has the potential to reduce future productivity [3]. These impacts make stunting a serious threat to the quality of human resources in Indonesia, hampering economic growth and exacerbating poverty rates [4]. Indonesia is a country facing a double burden of nutrition problems. According to 2020 data from JME, UNICEF, and the World Bank, Indonesia ranks 115th out of 151 countries in terms of stunting prevalence. The 2018 Basic Health Research (Riskesdas) data showed a stunting prevalence of 30.8%, while in 2019 it decreased to 27.7%. According to WHO standards, this figure still places Indonesia in the high category for stunting [2].

Bangka Belitung is one of the provinces in Indonesia experiencing an increase in stunting rates [5]. According to the 2022 Indonesian Health Survey, the prevalence of stunting in Bangka Belitung Province was 18.5% and increased again in 2023 by 2.1 percent to 20.6 percent [6]. The 2023 Indonesian Health Survey (SKI) revealed that stunting prevalence decreased in two regions: Central Bangka Regency and South Bangka Regency, while West Bangka Regency experienced a significant increase.

In 2016, the prevalence of stunting in West Bangka Regency reached 23.2% and increased to 25% in 2017. The prevalence of stunting among toddlers in Bangka Belitung Province in 2018 reached 12.1%. This figure may seem to have decreased compared to previous years in Bangka Belitung Province. However, in 2018, West Bangka Regency had the highest number of stunting cases, accounting for 18.4% of all regencies in Bangka Belitung Province [6]. By the end of 2024, there were still 822 children suffering from stunting spread throughout West Bangka Regency.

Stunting in toddlers requires serious attention because it can cause various impacts, such as stunted physical growth, delayed motor and language development, decreased intelligence, and increased susceptibility to infectious and non-infectious diseases. Furthermore, children with a history of stunting are at risk of low productivity as adults, are more susceptible to overweight and obesity, and in the long term, can increase the risk of developing degenerative diseases. Between 2016 and 2024, numerous studies examined factors related to stunting, and this issue remains a major concern for the Indonesian government in the health sector. However, these studies generally only used correlation analysis, which indicates the degree of closeness of the relationship between variables. Correlation analysis can illustrate associations, but it cannot explain causality. Therefore, the causal mechanisms underlying these factors have not been fully elucidated.

Causal modeling provides a fundamental overview of the interactions between factors within a problem and is a crucial aspect in various scientific fields [7]. To prevent stunting in toddlers, healthcare workers, including doctors, need to understand the origins and impacts of stunting. Therefore, an understanding of the causal mechanisms between factors related to stunting in toddlers is essential. Understanding this causal relationship is crucial so healthcare workers can focus more on the primary factors in providing preventative therapy. This study aims to develop a causal model of the factors causing stunting in toddlers. It is hoped that it will serve as a scientific reference for researchers, healthcare workers, and the government in formulating appropriate and effective policies and interventions to address stunting [8]. Specifically, this study uses a causal algorithm called the Peter-Clark Algorithm (PC-Algorithm). This algorithm searches for causal relationships by testing conditional independence between variables. This algorithm has two steps. In the first step, the PC algorithm starts with a complete graph and repeatedly removes edges connecting two variables if they are independent based on the conditional independence test, thus generating a skeleton. In the second step, the skeleton is directed, resulting in a causal model represented by a directed acyclic graph (CPDAG) [9].

This study refers to several previous studies that also used the GES and Peter-Clarak algorithms for causal modeling, such as: The first study entitled "Causal Modeling of Factors in Stunting Using the Peter Clark and Greedy Equivalence Search Algorithms" [10]. he study conducted causal modeling of eight parameters causing stunting in toddlers. The study showed that the GES algorithm could identify a causal relationship of 0.66 based on a comparison of directed density performance. The second study, entitled "Applying PC Algorithm and GES to Three Clinical Data Sets: Heart Disease, Diabetes, and Hepatitis" [9]. The results showed that the PC and GES algorithms were able to represent causal models of the three data sets.

## 2. Method

### 2.1 Research Stages

Research to identify the causal relationship of factors causing stunting was carried out in several research stages, which can be seen in **Figure 1.**

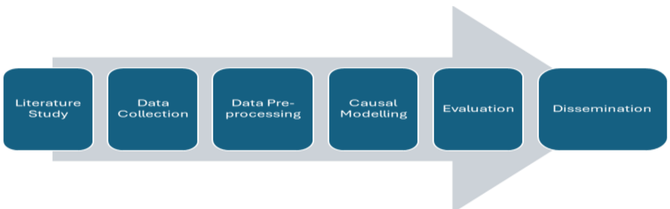


**Figure 1.** Research Stages

Based on **Figure *1***, the stages in this research include a study of related research literature, data collection, data pre-processing, causal modeling using the Peter-Clark Algorithm, evaluation, and dissemination. An explanation of each research stage is as follows:

1. Literature Study

   This phase began with a literature review to examine and understand the findings of previous studies as a foundation for this research. The results of this phase identified factors influencing stunting among toddlers in West Bangka Regency.

2. Data Collection

   Data collection in this study uses secondary data taken from the West Bangka Regency Health Office. The data collected is stunted toddler data in 2024. This study focuses on 13 factors, including: TB.U, BB.U, PBL, maternal education, maternal occupation, exclusive breastfeeding, visits to integrated health posts (Posyandu), immunization, maternal age at marriage, drinking water source, toilet ownership, family members smoking in the house, and maternal nutritional status during pregnancy.

3. Data Pre-processing

   The third stage in this research is data pre-processing, which aims to ensure the completeness of the data before the computational process is carried out. This process includes checking for missing values, identifying redundancy, cleaning the data, and selecting variables to be used in the analysis. This step is crucial to ensure the analyzed data remains clean and consistent, thus increasing the reliability of the built model. If missing data is found, corrections can be made by cleaning using the code New-Data <- Data[complete.cases(Data)].

4. Causal Modelling

   The next step in this research is causal modeling, which is a model that describes the cause-and-effect relationships between variables. In this study, causal modeling was performed using the Peter-Clark Algorithm, implemented in the R package "pclag."

   The Peter-Clark algorithm is an algorithm used to find causal relationships by testing conditional independence (CI) between variables. This algorithm has two stages: in the first stage, the PC algorithm starts with a complete graph or assumes that all variables are interdependent, followed by a process of removing edges that do not causally connect two variables and performing a conditional independence check on each pair of variables. Next, the algorithm performs edge orientation based on causal rules (such as the splitting rule) to determine the direction of the relationship so that only relevant edges remain. The final product of the Peter-Clark algorithm is a causal model represented in a directed acyclic graph (CPDAG) [9]. The pseudocode of the Peter-Clark algorithm is presented in **Figure 2.**

```
Algorithm 1 PC Algorithm
  Input Dataset D with a set of variables V and significant level α
  Output The undirected graph G with a set of edges E
  Assume all nodes are connected initially
  Let depth d = 0
repeat
  for each ordered pair of adjacent vertices X and Y in G do
    if |adj (X, G) \ {Y}| ≥ d then
      for each subset Z ⊂ adj (X, G) \ {Y} and |Z| = d do
        Test I (X, Y|Z)
        if I (X, Y|Z) then
          Remove edge between X and Y
          Save Z as the separating set of (X, Y)
          Update G and E
          break
        end if
      end for
    end if
  end for
  Let d = d + 1
until |adj (X, G) \ {Y}| < for every pair of adjacent vertices in G
```

**Figure 2.** Algoritma Peter-Clark

**Figure 2** shows that edges on variables X and Y are removed if they are proven to be independent of each other without considering the other variables. The different variables are then kept as separate sets in each iteration by increasing the depth of d and selecting a larger number of variables. This process will produce a graph depicting the causal structure of each variable if there are no more separable variables. The final result of the PC algorithm is a causal model with directed and undirected edges, mostly represented in a complete directed acyclic graph (CPDAG) that meets the edge-complete criterion. The rule is based on the notion of axiality and the fact that the selected variables produce a unique independent structure that allows for improvements to the structure of v.

5. Evaluation

The evaluation phase was conducted through a Focus Group Discussion (FGD) with a presentation of all the resulting causal models. The goal was to assess whether the resulting causal models remained appropriate and relevant to the scientific fields of health workers. The health workers targeted in this phase included nurses who treat stunted toddlers, nutritionists, doctors, lecturers with expertise in treating stunted toddlers, and community health workers.

In addition, the evaluation phase also examined the causal models generated using Causal Density (CD) and Directed Density (DD) to assess the representation of causal relationships occurring using the Peter-Clark Algorithm.

6. Dissemination

   The final stage of this research is dissemination. During the dissemination stage, the research results were implemented into a shiny website designed using the R programming language. This allows healthcare professionals to use it as an easy-to-understand reference for providing appropriate interventions for treating stunted toddlers.

## 3. Results and Discussion

### 3.1. Resutls

The results of this study are described to obtain a causal model using the Peter-Clark Algorithm (PC-Algorithm) method. The demographic characteristics of the research subjects are described based on gender, age, height (TB), weight (BB), Height/Age (TB/U), weight/Age (BB/U), PBL, Maternal Education, Maternal Occupation, Exclusive Breastfeeding, Posyandu Visits, Immunization, Maternal Age at Marriage, Drinking Water Source, Toilet Ownership, Family Members Smoking in the House, and Maternal Nutritional Status during Pregnancy. Details of the data set are presented in Error! Reference source not found..

```
> str(kausal)
'data.frame':	99 obs. of  13 variables:
 $ BB.U                           : int  11 11 11 11 12 8 7 13 14 10 ...
 $ TB.U                           : int  90 84 94 88 95 72 66 96 93 86 ...
 $ PBL                            : int  48 41 46 47 48 48 47 47 48 36 ...
 $ PendidikanIbu                  : int  0 1 0 1 0 0 3 1 2 1 ...
 $ PekerjaanIbu                   : int  1 1 1 1 1 1 1 1 1 1 ...
 $ ASIEksklusif                   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ KunjunganPosyandu              : int  1 1 1 1 1 1 1 1 1 1 ...
 $ Imunisasi                      : int  1 1 1 1 1 0 0 1 1 0 ...
 $ UsiaIbuMenikah                 : int  19 19 18 21 19 19 19 17 18 17 ...
 $ SumberAirMinum                 : int  1 2 2 1 2 1 1 1 1 1 ...
 $ KepemilikanJamban              : int  1 1 1 1 1 1 1 0 1 1 ...
 $ AnggotaKeluargaMerokokDalamRumah: int  1 1 1 1 1 1 1 1 1 1 ...
 $ StatusGiziIbuSaatHamil         : int  0 0 1 0 0 0 0 0 1 1 ...
```

**Figure 3.** Stunting data set details

Figure 3 shows the details of the variables in the stunting dataset. Next, the researchers performed data pre-processing to identify missing values before performing calculations. Missing data was checked using the code DataBaru <- Data[complete.cases(Data),] and variables to be calculated were identified based on the correlation values generated for each variable, using a 0.05 threshold for the PC algorithm. The distribution of stunting data for toddlers is presented in **Figure 4**.

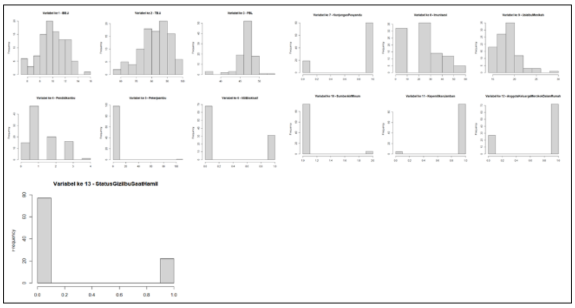

**Figure 4.** Distribution of Stunting Dataset

*Figure 4* shows the distribution of the stunting dataset, which consists of 13 variables. These variables will serve as the primary reference for identifying causal relationships. **Error! Reference source not found.** and **Error! Reference source not found.** show the results of causal modeling of the stunting dataset:

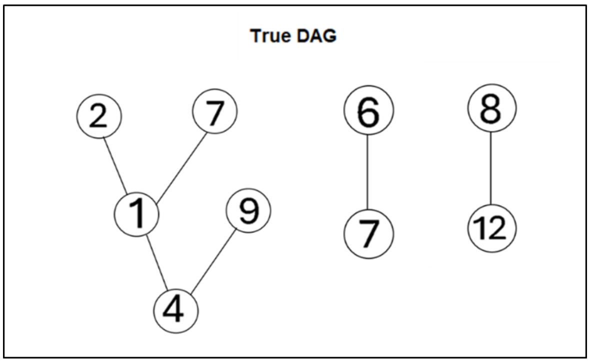


**Figure 5.** True DAG Visualization By PC-Algorithm

Figure 5 shows a visualization of the causal model using the PC-Algorithm method applied to the toddler stunting dataset, showing six relationships formed from eight variables. The causal model framework, called a "True DAG," indicates the existence of a causal relationship but does not yet display the direction of the relationship. A True DAG is a model generated by eliminating the direction of unnecessary nodes to obtain a good estimate of the model structure.

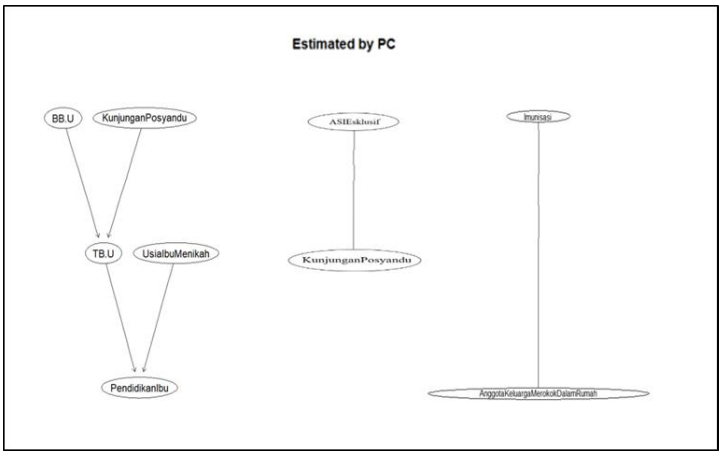

**Figure 6.** Causal Modeling of Stunting Using PC-Algorithm

Furthermore, Figure 6 shows six directional relationships, namely BB.U and TB.U, TB.U and Maternal Education, Maternal Age of Marriage and Maternal Education, Posyandu Visits and TB.U, Immunization and Family Members Smoking in the Home, and Exclusive Breastfeeding and Posyandu Visits. Next, an evaluation of the Peter-Clark algorithm was conducted using directional density identification and causal density, which were based on the model estimation results from the PC algorithm. The results of the causal modeling evaluation are presented in **Table 1.**

**Table 1.** Directed Density (DD) and Causal Density (CD) Evaluation Metrics

| Metric | PC Algorithm |
|---|---|
| DD | 4/6 = 0.66 |
| CD | 4/ 8(8-1) = 0.07 |

Table 1 shows the results of the Directed Density and Causal Density evaluation metrics for Peter Clark's algorithm. The evaluation results indicate that the PC algorithm is capable of identifying causal relationships 66% of the time. While these results are quite informative, 34% of the relationships remain undirected. Therefore, additional data, domain assumptions, or advanced algorithms (such as FCI or GES) are needed to determine their direction.

We implemented the results of this study into Shiny Web, which can be used by healthcare professionals as a reference to examine the relationship between factors causing stunting in toddlers in West Bangka Regency. Shiny Web also includes an explanation of the research results, which can be used as a reference for healthcare professionals in making decisions regarding appropriate therapy for treating stunting in toddlers. This web tool has several features, including data and methods, computational flow, computational results, and model visualization. **Figure 7** shows a display of the Shiny Web tool.

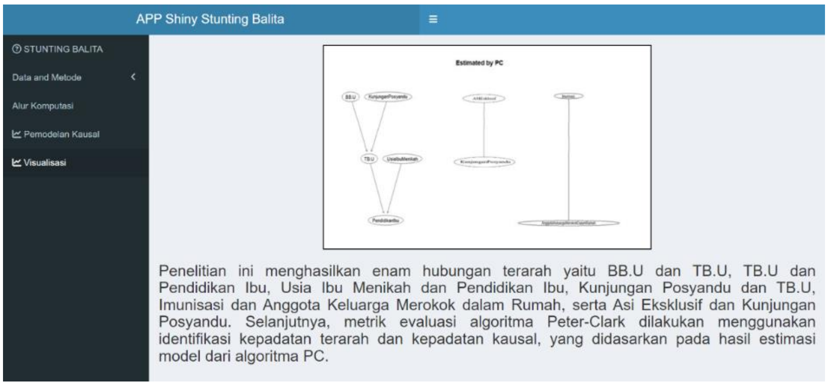

**Figure 7.** Toddler Stunting Website

### 3.2. Discussion

The results of the study above indicate that the BB.U variable is related to the TB.U variable to the incidence of stunting. Height that is not appropriate for age (low TB/A) is directly categorized as stunting [11]. Meanwhile, low body weight (BB/A) does not directly indicate stunting, but is an early signal of nutritional problems in toddlers. If low body weight is continuously low, height growth will be disrupted, leading to stunting [12]. Therefore, body weight acts as an early indicator or risk factor that, if left untreated, can lead to stunting. Meanwhile, infant height is the main indicator of the incidence of stunting in toddlers.

Another finding in this study is the variables of Integrated Health Post visits and TB.U on the incidence of stunting. Children who rarely visit Integrated Health Post have a risk of stunting three times higher than those who regularly attend. Low Integrated Health Post visits are directly related to growth failure (low TB/A), which defines stunting [13]. Regular attendance at Integrated Health Post supports improved physical growth, including height, which contributes to reducing the risk of stunting. Compliance with visits directly affects height-for-age, thus impacting stunting prevention. In general, research shows that regular visits to Integrated Health Post are correlated with better height growth and a reduced risk of stunting [14].

Furthermore, other variables that have a causal relationship are height for age and maternal education. Research conducted by [15] showed a significant relationship between maternal education level and the incidence of stunting in toddlers. This study found that mothers with higher education tend to have toddlers with better height for age. Maternal education is also related to parenting knowledge, nutritional access, family nutrition decisions, and responsive parenting, which contribute to children's physical growth. This is in line with the observation that maternal education is one of the social determinants that contribute to the reduction of stunting in the population. Maternal education has a strong and consistent relationship with child height growth (H/A) and the incidence of stunting. Mothers with higher education tend to be able to provide a better nutritional environment, so their children have optimal height growth and a lower risk of stunting [16].

Furthermore, another finding in this study is the relationship between age at marriage and maternal education with the incidence of stunting. In a study conducted by [17], it was shown that mothers who marry early have a higher risk of their children being short, thin, and having poor nutritional status. The study showed that the mother's age at first marriage has a significant negative effect on the likelihood of a baby experiencing stunting; the younger the age at marriage, the higher the risk of stunting. In addition, mothers with low education have a risk of stunting three times higher than mothers with higher education **[18].** Maternal education has been shown to be a strong determinant; a lack of education significantly increases the risk of stunting **[19].**

Furthermore, the findings in this study are the relationship between immunization and family members' smoking in the home. A study conducted by **[20]** showed a significant relationship between incomplete basic immunization and the incidence of stunting. Toddlers with incomplete basic immunization were shown to experience stunting more often than those with complete basic immunization **[21]**. Therefore, it can be said that complete basic immunization can support optimal growth and development and prevent stunting. In addition, the presence of family members who smoke in the home, especially fathers, is a potential predictor of stunting. Exposure to cigarette smoke at home is a significant determinant of stunting because smoking disrupts family nutrition (allocation of spending to cigarettes), worsens the child's respiratory environment, and increases the risk of infection **[22].**

Furthermore, there is a relationship between Exclusive Breastfeeding and Integrated Health Post Visits. A study conducted by **[23]** showed that toddlers who received exclusive breastfeeding for 6 months had a 0.83 times lower chance of stunting compared to those who did not. This means that exclusive breastfeeding is protective against stunting. Meanwhile, active Integrated Health Post visits are generally associated with a reduced risk of stunting, as they support growth and development monitoring and early intervention. However, the success of the program depends on the quality of services and the local context. The combination of exclusive breastfeeding and awareness and participation in Integrated Health Post(Posyandu) is an effective strategy in preventing stunting **[24].**

## 4. Conclusion

In this study, the authors applied the Peter-Clark Algorithm to cases of stunting in toddlers in West Bangka Regency. This study found a simple model representing the causal relationship between factors influencing stunting in toddlers, which is supported by previous research relevant to this study. The resulting model consists of six relationships: height (TB.U) and weight (BB.U), Integrated Health Post visits and height (TB.U), height (TB.U) and maternal education, maternal age at marriage and maternal education, immunization and family member smoking in the home, and exclusive breastfeeding and Integrated Health Post visits. This model not only finds correlation values but also establishes causal relationships between factors contributing to stunting in toddlers. The Peter-Clark algorithm in this study successfully identified causal relationships based on a comparison of performance using directed and causal density (67%). These results are quite informative, but 34% of the relationships were undirected. Therefore, additional data, domain assumptions, or advanced algorithms, such as FCI or GES, are needed to determine the direction. This causal model is expected to serve as a scientific reference for health professionals, such as doctors, nurses, midwives, nutritionists, researchers, toddler cadres, and others involved in managing stunting in toddlers. For further research, this model can be applied to other causal algorithms, which can generate more causal models that can provide broader insights into addressing the problem of stunting in toddlers.

## 5. *Acknowledgement*

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