# PRIORITIZING PREGNANT MOTHER AT RISK OF STUNTING: AN ANALYTIC NETWORK PROCESS APPROACH

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## ABSTRACT

Stunting occurs due to malnutrition which inhibits growth in toddlers. Stunting can also be caused by problems during pregnancy. This study aims to identify the risk of stunting during pregnancy and determine pregnant women who are at risk of this condition. By identifying and prioritizing critical factors that contribute to stunting in children under five, this research is expected to assist policy makers in developing effective solutions to reduce stunting rates. Handling the problem of stunting is important for the Government because it relates to the future generation of Golden Indonesia 2045. This study evaluates appropriate actions or therapies to reduce the risk of having children born with the potential to experience stunting. In the process of selecting pregnant women who are at risk of giving birth to children with the risk of stunting, a selection procedure is carried out that considers several factors such as the mother's age, mother's nutritional intake, arm circumference, hemoglobin level, parity, birth spacing, height, and mother's body mass index (BMI). The analytic network process (ANP) approach is used to determine the outcome of the selection process. The ranking is determined based on the calculation of the weighting of the criteria and sub-criteria in the ANP method. Based on the results of calculations using the ANP approach, PM 1 pregnant women get the highest score and are ranked first. These pregnant women are considered to have the highest risk of giving birth to babies with stunting risk.

**Keywords**: MADM, ANP, pregnant mother, stunting

## 1. PENDAHULUAN

The development of information technology and increasing complexity means that making effective decisions becomes a significant challenge. Especially when there is a problem that has many attributes or factors that must be considered before making a final decision. Decision making is an important challenge in various fields of life, including in the world of business, project management, environment, health, and others [1], [2] An effective and efficient decision-making process is very important to achieve the desired goals and minimize losses that may arise. Multi-Attribute Decision Making (MADM) is one approach that is growing rapidly in the field of decision making [1]. MADM focuses on situations where decisions must be made based on several interrelated criteria or attributes. MADM is an approach used to solve decision-making problems that involve many interrelated attributes. The main objective of MADM is to identify the best alternative from a set of choices based on predetermined criteria and to prioritize the alternatives based on their relative value to each given attribute. This method tries to measure and evaluate relevant attributes in a systematic and objective way [3]–[5]. In the MADM context, each attribute is weighted based on its importance. Then, the alternatives are assessed based on these attributes. This assessment can be done using quantitative techniques such as mathematical calculations, statistical analysis, or a model-based approach. The result of this process is the ranking of alternatives based on established criteria [2].

Health is an important need that can indirectly have an impact on the development of human resources in Indonesia that are more productive economically and socially. Various efforts have been made by the government to meet the needs of health services to the community, but until now these services have not been implemented optimally. Stunting is a widespread health issue affecting children, particularly in various regions worldwide [3]–[5]. It occurs when a child fails to reach the expected height, indicating insufficient nutrition or healthcare [6], [7]. The prevalence of stunting can be alarmingly high in certain countries, with estimates reaching up to 50% in locations like Papua New Guinea and Timor Leste, 45% in Pakistan, and 40% in Zambia. In other regions, stunting rates remain significantly high, although lower than the places, such as in India (39%), Nepal (37%), Indonesia (36%), Myanmar (35%), and Tanzania (35%) [5].

Stunting prevention measures can be taken before the birth of the baby. One way is to evaluate the criteria for the most influential causes of stunting [8]. These criteria can be broken down into sub-criteria that determine priority alternatives in efforts to resolve the stunting problem, so that it is hoped that the government will be more successful in achieving this goal.

The mother's role plays a crucial part in preventing stunting among children, a serious health issue that hampers a child's growth and leads to long-term health complications. Starting from the prenatal stage until the golden period of child development, encompassing pre-conception, prenatal, and infant-toddler phases, the mother's significant remains paramount [6], [9]. Thus far, mothers have undertaken various responsibilities to help mitigate the risk of stunting. These responsibilities include ensuring proper nutrition for both the mother and fetus, maintaining a balanced body mass index (BMI) for the mother, and avoiding psychosocial factors that can hinder growth and development. The age and overall health condition of pregnant women significantly influence the growth of a healthy fetus. Identifying pregnant women at risk of stunting can help minimize the occurrence of stunted births. This study aims to assess the condition of pregnant women, enabling appropriate treatment for those at high risk. Healthy pregnant women have a reduced chance of giving birth to stunted babies, thereby safeguarding the growth of their toddlers. By considering established criteria such as the mother's age, nutrition, hemoglobin levels, parity, birth spacing, height, and BMI, the likelihood of pregnant women delivering stunted babies can be minimized. Additionally, teenage mothers are more susceptible to malnutrition, which can lead to stunting. Monitoring nutrition and anthropometric measurements throughout pregnancy are essential. In a study [9], the weight gain in each trimester fell below expected levels based on baseline measurements, including height, weight, body mass index, and upper arm circumference [9]. These measurements serve as universal indicators of pregnancy risks, with thresholds set at heights below 150 cm, body weights below 45 kg, BMI below 18.5 kg/m2, and upper arm circumferences below 23.5 cm. Other risk factors include the age of the pregnant woman, the number of previous pregnancies, and the spacing between pregnancies. Numerous risk factors contribute to stunting in pregnant women.

In line with the development of information technology, efficient and accurate decision making is the key to success in various fields. In this context, Multi Attribute Decision Making (MADM) has become an important and rapidly growing area of research. MADM is an approach used to make decisions based on several relevant attributes or criteria. Multi-Attribute Decision Making (MADM) has been the subject of extensive and in-depth research across various disciplines. MADM has many applications in various fields, including business, management, engineering, social sciences, and the environment [10], [11]. Several related studies have been carried out by researchers by applying the MADM method to address complex decision-making problems. These studies provide deeper insight and understanding of the potential and application of MADM in various contexts. Several relevant studies using MADM in various contexts have been carried out by many researchers. These studies provide evidence about the application and advantages of MADM in decision making[1], [12]. The use of MADM in research conducted by  can improve decision-making performance in vertical handover by considering several important attributes such as signal strength, quality of service, and cost. [11] in their research using the MADM approach based on utility and reputation functions can improve the quality of decision making in the context of selecting a multi-access access network by considering factors such as speed, latency, and quality of service.

In complex decision-making research, the Analytic Network Process (ANP) method is widely used. [13] have conducted research aimed at developing a decision-making tool that utilizes ANP. In this study, the ANP method was used to analyze and evaluate various factors related to the design of wildlife corridors, such as size, sustainability, connectivity, and implementation costs. The results of this study provide guidance in selecting the optimal wildlife corridor design from the various alternatives available. The same method has also been developed in the research conducted by [14] using ANP to analyze and assess various factors relevant to wind energy capacity development, including technical, environmental, economic, and social factors. The results of this study provide information for policy makers and decision makers in determining the optimal priority strategy in expanding wind energy capacity in Turkey. [15] made an important contribution in the use of ANP in decision making. They combine strategic choice and ANP approaches to address the complexities of decision-making involving data and values. Using this approach can provide a holistic framework for dealing with complex decision-making problems and help stakeholders to consider both factual and value aspects in the decision-making process. Research conducted by [16] uses ANP as a framework for assessing and mitigating risk in large-scale construction projects. This research applies a model-based approach to identify, measure, and manage risks associated with large-scale construction projects. The results of this study provide useful guidance for project developers and decision makers in managing risk more effectively.

## 2. METHOD

The Analytic Network Process (ANP) method is a development of the AHP method, which can accommodate interrelationships in the form of interaction and feedback from elements in a cluster (inner dependence) or between clusters (outer dependence). ANP is a method of solving an unstructured problem and there is a dependency relationship between its elements. The concept of ANP was developed from AHP theory which is based on the interdependence relationship between several components. The main concept in ANP is influence, while the main concept in AHP is preference [17]–[19].

Hierarchical arrangements are not applicable to numerous decision problems due to the complex interactions and dependencies between higher-level and lower-level elements. The significance of an alternative cannot solely be determined by its own level of importance [20]. The structure of this feedback system does not follow a traditional top-down hierarchy but instead takes the form of a network with interconnected components and cycles. It also comprises source and sink nodes. The source node serves as the starting point of an influence path and is never the endpoint. Conversely, the sink node represents the endpoint of an influence path and never serves as a source for existing paths. Figure 1 provides an illustration of a feedback network structure.

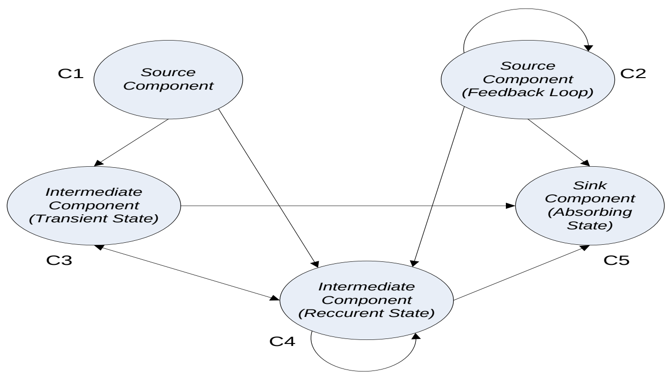



**Fig.1**. Feedback Network Structure

The nodes represent a collection of criteria and alternatives, they can be seen in figure 1. Source components, such as C1 and C2, are components that do not have incoming arrows. Sink components, like C5, are components that do not have outgoing arrows. Transient components, such as C3 and C4, have arrows both entering and exiting the node. Notably, C3 and C4 form a cycle between them, as they provide feedback to each other. C2 and C4 have loops that connect them back to themselves, known as inner dependencies. Other connections between components are referred to as outer dependencies.

The components of the decision network are denoted as Ch, where h ranges from 1 to m. Each component is assumed to consist of nh elements, represented as eh1, eh2, ..., ehmh. The impact of a specific set of elements within a component on each element in the system is represented by the priority vector resulting from pairwise comparisons using the Analytic Hierarchy Process (AHP) methodology. These priority vectors can be used to construct a matrix that illustrates the flow of influence between component elements, both within the component itself and with other elements. The influence of elements within the network on other elements can be observed through equation 1.

$$W = \begin{bmatrix} W_{11} & W_{12} \ldots & W_{1m} \\ W_{21} & W_{22} \ldots & W_{2m} \\ \vdots & \vdots & \vdots \\ W_{m1} & W_{m2} \cdots & W_{mm} \end{bmatrix} \quad (1)$$

n equation 1, the priority vector values for the C1 component, composed of elements e11, e12, ..., e1n1, are represented in the first row and first column. Similarly, the priority vector values for the

C2 component, consisting of elements e21, e22, ..., e2n2, are displayed in the second row and second column. The priority vector values for the Cm component, which comprises elements em1, em2, ..., emnm, are indicated in the last row and last column.

Wij's input data in the super matrix is called a block. The block is a matrix with the arrangement as in equation 2

$$W_{ij} = \begin{bmatrix} w_{i_1 j_1} & w_{i_1 j_2} \cdots & w_{i_1 j_{nj}} \\ w_{i_2 j_1} & w_{i_2 j_2} \cdots & w_{i_1 j_{nj1}} \\ \vdots & \vdots \cdots & \vdots \\ w_{i_n j_1} & w_{i_n j_2} \cdots & w_{i_{n11} j_{nj}} \end{bmatrix} \quad (2)$$

Equation 2 illustrates the level of impact that one element has on other elements. Certain values may be null, indicating that the element has no effect on a specific element. Elements that influence themselves are assigned a value of one.

In general, the interest relationship between elements and other elements in the network can be represented following the supermatrix, as follows:

$$\mathbf{W} = \begin{array}{cc} & \\ C_1 & \begin{array}{c} e_{1_1} \\ e_{1_2} \\ \vdots \\ e_{1_{n_1}} \end{array} \\ C_2 & \begin{array}{c} e_{2_1} \\ e_{2_2} \\ \vdots \\ e_{2_{n_2}} \end{array} \\ \vdots & \\ C_m & \begin{array}{c} e_{m_1} \\ e_{m_2} \\ \vdots \\ e_{m_{n_n}} \end{array} \end{array} \begin{bmatrix} W_{1_1} & W_{1_2} & \cdots & W_{1_m} \\ W_{2_1} & W_{2_2} & \cdots & W_{2_m} \\ & & \vdots & \\ W_{m_1} & W_{m_2} & \cdots & W_{m_m} \end{bmatrix} \quad (3)$$

Determination the priority limit of the super matrix, it needs to be transformed into a matrix where each column contains equal numbers. The priority of an element in a component serves as an indication of the component's priority based on the influence it has on other components in the super matrix. Each comparison generates a priority vector that reflects the influence of all components on the left-hand side of the super matrix on the component at the top of the super matrix. This process is repeated for each component. The resulting vector is used as a weighting factor for the matrix block in the corresponding component's column. The first input is multiplied by all the elements in the second block, and so forth. The outcome of this procedure is known as a weighted super matrix, where each column contains uniform values. This Weighted Super matrix can be employed to obtain the desired priority by transforming it into a limit matrix through iteratively squaring the super matrix until the values in the columns converge to the same number.

## 3. Result And Discussion

The aim of selecting pregnant women at risk of giving birth to stunted babies is to identify those with minimal risk and ensure appropriate treatment for those at high risk. This study aims to assess the risk of pregnant women and provide timely intervention for those at risk. Healthy pregnant women are expected to have a low risk of giving birth to stunted babies, thus promoting healthy growth in toddlers. To minimize the risk of stunted babies, certain criteria need to be considered. These criteria include Ct1 (maternal age), Ct2 (maternal nutrition), Ct3 (arm circumference), Ct4 (hemoglobin levels), Ct5 (parity), Ct6 (birth interval), Ct7 (height), Ct8 (baby weight), Ct9 (BMI). Additionally, teenage mothers are more susceptible to malnutrition, which increases the risk of stunting. Monitoring nutrition and measuring physical characteristics during different stages of pregnancy, such as weight gain, height, body mass index (BMI), and upper arm circumference, can help identify potential risks. These measurements serve as universal indicators with specific thresholds for height (below 150 cm), body weight (below 45 kg), BMI (below 18.5 kg/m2), and upper arm circumference (below 23.5 cm) [23]. Risk factors also include maternal age, number of previous births, and inter-pregnancy interval. Numerous risk factors contribute to the possibility of having a stunted baby in pregnant women.

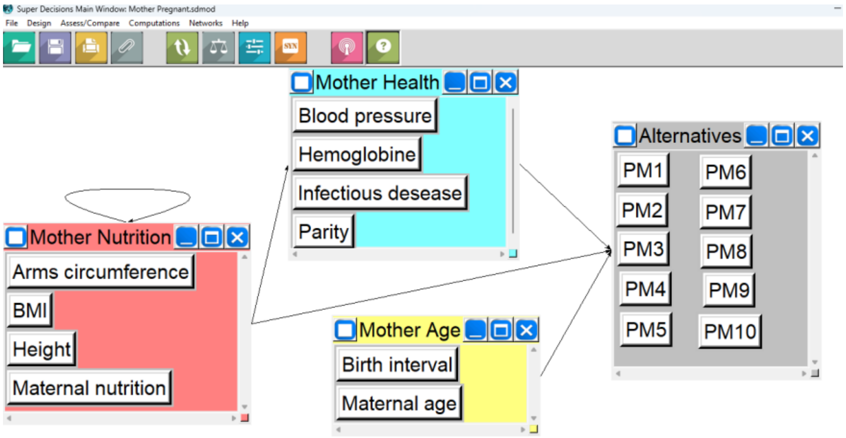



**Fig.2**. Representation of Problems in Cluster Network

In the network structure of the ANP method in figure 2 it can be seen the interrelationships between groups or clusters or between elements or nodes in the same group or in other groups. A cluster is automatically connected to each other because of the relationship between its member nodes.

The subsequent stage involves calculating the priorities for each formed group or cluster. Based on the network representation matrix, elements, or nodes with a value of one generate a specific value through the calculation of inter-group priorities. Table 1 provides an overview of the pairwise comparison values and priority weights for each cluster linked to the alternative cluster.

**Table 1. Pairwise Comparison of Alternative Cluster Interests**

| | *Mother Nutrition* | *Mother Health* | *Motherr Age* | *Prioritas* |
|---|---|---|---|---|
| **Mother Nutrition** | 1 | 2 | 2 | 0,666667 |
| **Mother Health** | 0,5 | 1 | 2 | 0,333333 |
| **Mother Age** | 0.5 | 0.5 | 1 | 0,333333 |

*Ratio Consistency* = 0

Calculations and analysis on the clusters show that the mother health cluster is more important than mother nutrition. The resulting consistency ratio is 0 so it is stated that the comparison matrix given is consistent.

The pairwise comparison values and priority weights for each group (cluster) connected to the Mother Nutrition cluster can be seen in table 2. From the comparative analysis of the interests of the Mother Nutrition cluster, the maternal nutrition cluster is the most important of the other clusters and the comparison matrix given is consistent. The resulting pairwise comparison matrices are consistent because the consistency ratio (CR) is less than 10 percent.

**Table 2. Pairwise Comparison of Mother Nutrition Cluster Interests**

| | *Alternative* | *Arm Circumfefence* | *BMI* | *Height* | *Maternal Nutrition* | *Priority* |
|---|---|---|---|---|---|---|
| **Alternatif** | 1 | 0,2 | 0,142857 | 2 | 0.33333 | 0,096309 |
| **Arm Circumference** | 5 | 1 | 0,333333 | 3 | 5 | 0,265637 |
| **BMI** | 7 | 3 | 1 | 5 | 3 | 0,557855 |
| **Height** | 0,5 | 0,333333 | 0,2 | 1 | 0.33333 | 0,080198 |
| **Maternal Nutrition** | 3 | 0.2 | 0.333333 | 3 | 1 | 0,701437 |

*Consistency Ratio* = 0,084689

The same steps are used to calculate the importance ratio for the other clusters. The priority values of the group (cluster) are arranged in a matrix called the cluster matrix as shown in table 3.

**Tabel 3. Cluster Matrix**

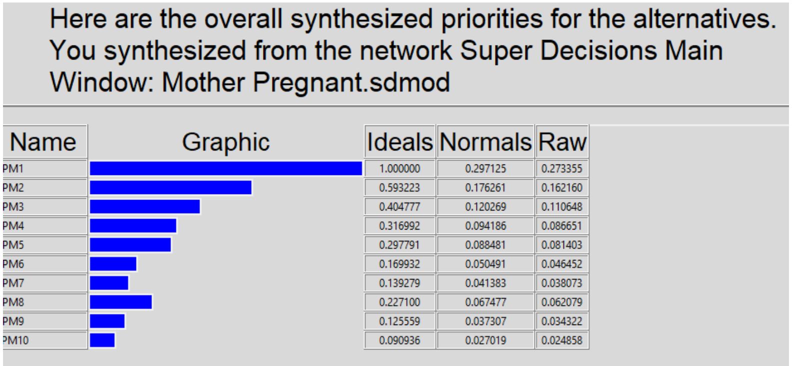
| *Cluster* | *Alternative* | *Mother Health* | *Mother Nutrition* | *Mother Age* |
|---|---|---|---|---|
| **Alternative** | 0 | 0,096309 | 0,085324 | 0,1666667 |
| **Mother Health** | 0,666667 | 0 | 0,265637 | 0,833333 |
| **Mother Nutrition** | 0,333333 | 0,213238 | 0 | 0.4654 |
| **Mother Age** | 0.27111 | 0.0766 | 0.0662 | 0 |

Pairwise comparison of nodes in Alternative Clusters is the next step that must be calculated. Elements (nodes) that are connected to alternatives are related so that they have a pairwise comparison value. From the calculation results, the priorities of these nodes against alternatives can be seen in table 4.

**Table 4. Priority of Nodes to Alternatives**

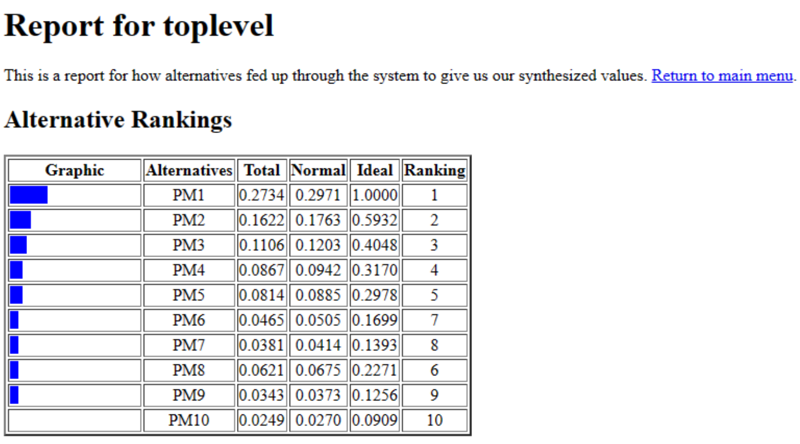
| Element(*node*) | Alternatives | | | | | Consistency Ratio (CR) |
|---|---|---|---|---|---|---|
| | ***PM1*** | ***PM2*** | ***PM3*** | **…** | ***PM10*** | |
| **Arms circumference** | 0,118474 | 0,248778 | 0,55016 | … | 0,082588 | 0,03909 |
| **BMI** | 0,208275 | 0,101044 | 0,642682 | … | 0,048 | 0,064448 |
| **Height** | 0,134062 | 0,053799 | 0,259473 | … | 0,552665 | 0,067539 |
| **Maternal nutrition** | 0,124377 | 0,297066 | 0,520472 | … | 0,058084 | 0,02575 |
| **Blood pressure** | 0,066493 | 0,294046 | 0,520866 | … | 0,118595 | 0,071208 |
| **Hemoglobin** | 0,067962 | 0,323789 | 0,456019 | … | 0,152231 | 0,038811 |
| **Infectious disease** | 0,116652 | 0,338899 | 0,478218 | … | 0,066232 | 0,082596 |
| **Parity** | 0,116652 | 0,338899 | 0,478218 | … | 0,066232 | 0,082596 |
| **Birth interval** | 0,515922 | 0,249334 | 0,182415 | … | 0,052329 | 0,050184 |
| **Maternal age** | 0,511689 | 0,078018 | 0,237814 | … | 0,173479 | 0,038872 |

The next step is to put the weight of each node into a matrix that contains all the elements (nodes) so that the dimensions of the matrix formed are large, so it is called a super matrix. The initial super matrix formed is called an unweighted super matrix. Calculation results of unweighted super matrix. The super matrix is then made so that when the column elements are added together, they produce one by normalizing it, namely multiplying the unweighted super matrix by the cluster matrix according to the cluster in question.


Here are the overall synthesized priorities for the alternatives. You synthesized from the network Super Decisions Main Window: Mother Pregnant.sdmod

| Name | Graphic | Ideals | Normals | Raw |
|---|---|---|---|---|
| PM1 | | 1.000000 | 0.297125 | 0.273355 |
| PM2 | | 0.593223 | 0.176261 | 0.162160 |
| PM3 | | 0.404777 | 0.120269 | 0.110648 |
| PM4 | | 0.316992 | 0.094186 | 0.086651 |
| PM5 | | 0.297791 | 0.088481 | 0.081403 |
| PM6 | | 0.169932 | 0.050491 | 0.046452 |
| PM7 | | 0.139279 | 0.041383 | 0.038073 |
| PM8 | | 0.227100 | 0.067477 | 0.062079 |
| PM9 | | 0.125559 | 0.037307 | 0.034322 |
| PM10 | | 0.090936 | 0.027019 | 0.024858 |

**Fig.2.** Alternative Priority Synthesis Results


## Report for toplevel

This is a report for how alternatives fed up through the system to give us our synthesized values. Return to main menu.

### Alternative Rankings

| Graphic | Alternatives | Total | Normal | Ideal | Ranking |
|---|---|---|---|---|---|
| | PM1 | 0.2734 | 0.2971 | 1.0000 | 1 |
| | PM2 | 0.1622 | 0.1763 | 0.5932 | 2 |
| | PM3 | 0.1106 | 0.1203 | 0.4048 | 3 |
| | PM4 | 0.0867 | 0.0942 | 0.3170 | 4 |
| | PM5 | 0.0814 | 0.0885 | 0.2978 | 5 |
| | PM6 | 0.0465 | 0.0505 | 0.1699 | 7 |
| | PM7 | 0.0381 | 0.0414 | 0.1393 | 8 |
| | PM8 | 0.0621 | 0.0675 | 0.2271 | 6 |
| | PM9 | 0.0343 | 0.0373 | 0.1256 | 9 |
| | PM10 | 0.0249 | 0.0270 | 0.0909 | 10 |

**Fig.4.** Rank of Alternative

The results of processing using the Super Decisions software for the ANP method, it was found that Mother Pregnant 1 (PM1) had the highest priority. This means that PM1 has the greatest risk of giving birth to stunted babies.

## 4. CONCLUSION

Stunting in children is a serious problem that can have a negative impact on their growth and development. Therefore, it is important to identify and prioritize pregnant women who are at risk of experiencing stunting to carry out appropriate interventions to prevent stunting in the children to be born. In this study, the Analytic Network Process (ANP) approach was used to develop a framework for prioritizing pregnant women at risk of stunting.

This study provides a comprehensive view and methodology that can be used to prioritize pregnant women at risk of stunting. By identifying the most influential factors and paying special attention to these aspects, it is hoped that it can reduce stunting rates in children born to at-risk mothers. Collaborative efforts between government, medical personnel and society are urgently needed to achieve this goal and ensure optimal health and development for future generations.

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