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Artificial Intelligence-Enabled Predictive Insights for Ameliorating Global Malnutrition: A Human-Centric AI-Thinking Approach

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Abstract: According to the World Health Organization (WHO) and the World Bank, malnutrition is one of the most serious but least-addressed development challenges in the world. Malnutrition refers to the malfunction or imbalance of nutrition, which could be influenced not only by under-nourishment, but also by over-nourishment. The significance of this paper is that it shows how artificial intelligence (AI) can be democratized to enable analysts who are not trained in computer science to also use human-centric explainable-AI to simulate the possible dynamics between malnutrition, health and population indicators in a dataset collected from 180 countries by the World Bank. This AI-based human-centric probabilistic reasoning approach can also be used as a cognitive scaffold to educe (draw out) AI-Thinking in analysts to ask further questions and gain deeper insights. In this study, a rudimentary beginner-friendly AI-based Bayesian predictive modeling approach was used to demonstrate how human-centric probabilistic reasoning could be utilized to analyze the dynamics of global malnutrition and optimize conditions for achieving the best-case scenario. Conditions of the worst-case "Black Swan" scenario were also simulated, and they could be used to inform stakeholders to prevent them from happening. Thus, the nutritional and health status of vulnerable populations could be ameliorated.

Keywords: malnutrition; World Bank; health; population; Bayesian; predictive modeling; artificial intelligence; human-centric; human in the loop; AI-Thinking; explainable-AI; AI for good

1. Introduction

1.1. How Policy Making can be Informed by Unified Analytics of Nutrition, Health, and Population Statistics

In the context of a changing global nutrition landscape influenced by globalization, demographic shifts and income growth, diet-related epidemiology has seen a significant shift in recent decades. The double burden of malnutrition now facing many countries worldwide is characterized by the coexistence of undernutrition along with overweight, obesity or diet-related noncommunicable diseases [1,2]. In many countries, these different types of malnutrition co-exist at the national and household levels and across the life course. In the 2018 Global Nutrition Report, nearly 2 billion adults worldwide were overweight and obese, with a further 2 billion suffering from micronutrient deficiency. An estimated 38.3 million under five year olds are now overweight and obese, 150.8 million are stunted, and a further 50.5 million are wasted [3]. The developmental, economic, social and medical impacts of this global burden of malnutrition are serious and lasting for individuals, their families, and countries. Today, nearly one in three persons globally suffer from at least one form of malnutrition: wasting, stunting, vitamin and mineral deficiency, overweight or obesity and diet-related non communicable diseases [1–3]. Nutrition-related factors contribute to approximately 45% of deaths in children aged under 5 years (mainly due to undernutrition), while low- and middle-income countries are now witnessing a simultaneous rise in childhood overweight and obesity [4–6].

Nutrition is critical to both health and economic development. Both undernutrition- and obesity-related diseases contribute substantially to the burden of disease in these societies. The direct and indirect economic costs incurred by individuals and populations are often unsustainable and contribute a significant barrier to economic and social development. Malnutrition could have adverse effects on health, which could result in increased health-care costs, reduced productivity, and lower economic growth. This could in turn perpetuate a cycle of poverty and ill-health. The double burden of malnutrition confers a serious and negative economic impact on individuals and populations. As the burden of malnutrition continues to rise, so too does its economic toll.

While the double burden of malnutrition may pose a significant public health challenge, it also offers a unique opportunity for alignment and coordination for integrated action on malnutrition in all its forms. The identification of the double burden of malnutrition should be regarded as a catalyst for the achievement of key global goals for addressing policy and program interventions.

Determining the approach to care is essential in the evaluation of the performance of health care delivery and its rational planning. Understanding the dynamics between the indicators of population health statistics, economic, and access to health services is fundamental in the evaluation of the effects of ongoing changing health care delivery systems. Unmet health needs may be especially significant for minority population groups, such as children, the elderly or pregnant women. Policy making have previously been informed by studies examining the relationship between socioeconomic status, gender differences in disease incidence and access to health services [7–9].

Beyond debate, however, is the need for improved knowledge on nutrition, health, and population statistics to inform policy makers on a broad base issue related to public health planning, health care reform and the evaluation of health care delivery. To contribute to this worthy endeavor, the World Bank has made the malnutrition, health, and population statistics dataset publicly available [10].

Even though the dataset collected by the World Bank contains data from all the countries in the world, a realistic problem faced by analysts (e.g., health professionals, policymakers and researchers) using null hypothesis significance testing (NHST) frequentist approaches is that they might not yield statistically significant results if there are relatively few aggregated data (e.g., only 19 rows of data from the years 2001–2018) at the global system level. They may not be able to conclude with certainty the consequences, efficacy, aptness, and costs of care for segments of the population and for disparate structure of health care delivery and compensation. When this is so, they are unable to say with assurance about the value of the investment in health care for population subgroups, regions, or nations. In principle, characteristics in nutrition, health, and population statistics can be learned, albeit in piecemeal perspectives via a non-unified analysis through numerous avenues, such as surveys, disease registries, computer-based patient records and electronic financial transactions for health insurance claims. In practice, no particular avenue will produce knowledge appropriate for every research question.

To overcome this hurdle, a rudimentary AI-based approach will be illustrated to suggest how artificial intelligence (AI) [11], and specifically, explainable-AI (XAI) [12], can assist in the intuitive use of human-centric probabilistic reasoning to interpret the counterfactual results generated by predictive models. AI-based analytics warrant a reasonably comprehensive source of the information needed to determine regional health needs, assess the patterns of illness, and predict patterns of health care spending. AI-based analytics can achieve this by predicting knowledge on health trends, costs and the effectiveness and quality of health care services. AI-based analytics can also contribute to improvements in quality of care by making information available to institutions and user groups for their use in quality improvement programs for regional health planning. AI-based analytics is useful in addressing policy questions and national debate related to health care reform.

The latter part of this paper explores a predictive modeling approach based on AI to investigate how malnutrition analysts can use AI-assisted probabilistic reasoning to view counterfactual scenarios that could potentially be used to inform policy making. However, human beings must take the lead in the use of AI instead of being unquestionably led by AI. Therefore, the notion of human-centric AI-Thinking will be discussed in the next section to facilitate this discourse.

1.2. The Theoretical Basis of AI-Thinking

AI-based advanced data analytical methods, such as unsupervised, semi-supervised and supervised machine learning, are capable of discovering the associations in datasets between variables. Until the emergence of machine learning, this has been a laborious task for humans to accomplish. It does not imply, however, that people can be replaced with AI. In interpreting the findings produced by the AI software, it is imperative for humans to play the leading role, especially if AI continues to be developed into more powerful superintelligence [13]. Human beings must continue to play a vital role, because we possess the capacity of linking together domain knowledge that straddles both AI and human-centric realms. The notion of this way of thinking and knowing—AI-Thinking—was first offered by Zeng [14] as a framework that could be used to leverage cognitive computing data analytics and thus enhance learning by challenging humans to interpret new findings from the machine-learned discovery of hidden data patterns. The interplay between the use of artificial intelligence and its use in education has been observed to be engaging for learners [15] and is capable of educing (drawing out) AI-Thinking [16]. Educators also want to inculcate AI-Thinking [14,17] in learners, as AI has been shown to be beneficial in engaging learners to generate more questions when they discover the machine-learned hidden relationships among data variables [18].

The term AI-Thinking could be interpreted as follows in the context of the current paper. “AI” refers to machine-based artificial intelligence, while “thinking” refers to human-in-the-loop (HuIL) [19] reasoning. AI-Thinking could enable nutrition professionals to identify opportunities for applying AI and to collaborate with multidisciplinary experts to inform policymaking. To grasp and interpret AI's scientific findings in meaningful human-centered terms, nutrition consultants should be sufficiently informed about the technical details of how the AI interpreted the data (e.g., in this case, to be at least familiar with how the Bayesian theorem's mathematical algorithm works).

AI-Thinking is not a linear process of thought. The notion of learning can be considered as a type of complex phenomenon in education [20]. It could be interpreted as the co-emergence of at least two major simultaneous forms of thought that enter a state of “vital simultaneities” [21], that is, in human-initiated AI analysis on the dataset informing human-centric reasoning, and vice-versa, in human-centric reasoning informing further AI analysis on the dataset. They are inextricably bound together and cannot easily be separated from each other. However, even though AI-Thinking is elusive and complex, it is essential to note that the need to educe AI-Thinking for harnessing AI, especially for social good, could not be overstated, as educational programs are rapidly being implemented in a period of time where the use of AI is beginning to gain traction worldwide.

1.3. Democratizing the Use of AI for Analysts Who are not Computer Scientists

AI was more closely associated with the departments of computer science in universities than with departments engaged in malnutrition-related studies. However, AI has gained so much traction across industries in recent years that it is known as Industry 4.0. It underlines the value of training people not only to solve problems using foundational principles that they know from any particular discipline, but also from AI. The supporting role of AI as educational scaffolds for the training of analysts who are not computer scientists will lead to their better understanding of AI for asking better questions [22]. Many educators in various academic disciplines, in addition to the computer science faculties, have tried to introduce common AI principles, such as machine vision, natural language processing (NLP), machine learning (ML), deep learning (DL), and reinforcement learning (RL). Subsequently, these learners could be trained to create artificial neural networks (ANN), recurrent neural networks (RNN), convolutional neural networks (CNN), or generative adversarial networks (GAN). However, Correa, Bielza, and Pamies-Teixeira [23] point out the interactions between the nodes in artificial neural networks could be likened to a black box. Either they are concealed, or they are far too complicated to be easily understood by humans. Scientists and analysts who may not be computer scientists also need to be trained with AI-enhanced data-driven evidence-based human-centric reasoning skills so that they can function in teams and interact with one another intuitively to address topics relevant to malnutrition, health, and population statistics. Therefore, in the current paper, another AI-based approach that can provide support to human-centric thinking—AI Thinking—will be presented.

2. Research Problem, Research Questions, and Model

2.1. Research Problem

Despite the importance of acquiring knowledge in AI, the field of AI is not easily understood by people who are not computer scientists. Moreover, data analytics has emerged as a professional skill that potential employers expect their employees to possess, irrespective of whether they have been formally taught in school [24]. It behooves one to wonder: is there a more intuitive human-centric reasoning method for students that is relatively easy to use, so that people who may not be too comfortable with computer programming or advanced mathematics can also use AI to analyze data and interpret the results? In addition, is there any user-friendly AI-based program that could be used by practitioners to pose theoretical questions, perform simulations with different variables in various computational modeling situations and then discuss their theories with peers based on the outcomes of the analyzed data? Can the AI software utilize logical human-centric reasoning that could also be easily understood by individuals who are not computer scientists or mathematicians (e.g., policy makers)? The current paper suggests that there is one approach of this kind that might be worth considering. This paper proffers an AI-based Bayesian Network (BN) probabilistic reasoning approach [25–27] using a user-friendly software which is suitable for beginners. Instead of trusting unquestionably in the findings provided by AI, though, people should and could take the lead. e.g., by carefully analyzing the models and results produced by AI using the conceptual notions of AI-Thinking.

Logical reasoning, probabilistic reasoning and deep data-driven learning are the main theoretical paradigms that have shaped research in AI-Thinking [28]. AI-Thinking is involved cognitively in the use of AI as a method for research, in dynamic representations of complex knowledge, and in AI-development [29]. Using AI-Thinking, probabilistic reasoning with data-driven computational models is more intuitive for understanding the complexities in real-world issues, as probabilistic reasoning is similar to the natural process of human thinking [17].

In consideration of this, the details in the current paper are intended to provide opportunities to educe (draw out) AI-Thinking in the learners in terms of logical reasoning (e.g., how the prediction and subsequent re-adjustment of variables in the health or population levels could potentially lead to better or worse levels of nourishment), probabilistic reasoning (e.g., via the Bayesian probabilistic reasoning approach), and deep data-driven learning (e.g., discovery of hidden patterns of the relationships between the variables of the malnutrition, health, and population statistics via machine learning of the dataset).

BN's primary advantage is that its powerful probabilistic approach allows users to develop an intuitive understanding of the processes involved. Given observations of evidence in the BN, questions can be raised to assess the posterior probability of any variable or group of variables. However, the current paper does not intend to make comparisons between the usage of BN and ANN in predictive models; as that has already been well documented by Correa, Bielza, and Pamies-Teixeira [23], who observed that BN can explain the relationships that occur between the nodes in a model better than black box-like ANNs.

To demonstrate how human-centric AI-Thinking can be applied as an educational scaffold, the current paper will show how the probabilistic results generated by a rudimentary BN model can be interpreted. The BN model will be used to measure the direct and/or integrative effects the variables from the health and population dataset may have on the outcome (various levels of the "severity" of malnutrition). For predictive applications in the modeling of real-world scenarios, BN modeling has been known for delivering good and reliable performance [30,31].

2.2. Research Questions

The three over-arching research questions that guide the current paper are:

- **RQ1:** From descriptive analytics of the dataset, what are the characteristics of the state of global malnutrition between the years 2001 and 2018?
- **RQ2:** From predictive analytics of the dataset, what is the best-case scenario that could result in low malnutrition levels in the global population?
- **RQ3:** From predictive analytics of the dataset, what is the worst-case scenario that could result in high malnutrition levels in the global population?

2.3. The Research Model

The primary goal of the current paper was to provide one of countless possible ways to educe AI-Thinking (regardless of how much or how little) to theoretically inform additional analyses and policy making. The goal of the examples is not to advocate the Bayesian Network as the strongest explainable AI method, but to provide rudimentary examples to encourage analysts to think broadly about the trustworthiness of AI-based analytical techniques, and exercise AI-Thinking to address issues about malnutrition, health, and population statistics with stakeholders. In other words, raising questions and focusing on the possibilities for problem-solving is far more important than trying to find the so-called right answer.

The methods of probabilistic reasoning used are based on BN. The Bayesian approach has been chosen because it is a methodology used to model the performance of systems in which the Markov blanket concept [32], in conjunction with Response Surface Methodology (RSM) [33–36] are utilized. Together, they are proven methods that can be used to analyze the optimization of the relationships between the theoretical constructs (variables) and the target (levels of malnutrition), even if they are not physically related.

The current paper presents an approach to promote discussions on AI and malnutrition health and population statistics using descriptive analytics as well as predictive simulations, using data shared by the World Bank [10].

The detailed BN models on malnutrition, health and population statistics are presented in the subsequent sections. The current paper suggests a basic Bayesian method to show how researchers involved in malnutrition health and population statistics—rather than computer scientists—could also use AI-based methods to investigate any possible hidden motif in the data, so that the dynamics of the system can be analyzed via predictive simulations to learn about its theoretical "behavioral" boundaries [37]. Two forms of analytics will be shown using a semi-supervised machine learning BN model to achieve the following:

2.4. Descriptive Analytics of "What Has Already Happened?"

Purpose: To discover the motifs of the data collected, using descriptive analytics. For descriptive analysis, BN modeling employs the parameter estimation algorithm for estimating the distribution of data of each column in the dataset automatically. Further, curve analysis and Pearson correlation analysis will also be used to learn more about current conditions of malnutrition, health and population statistics variables.

2.5. Predictive Analytics Using "What-If?" Hypothetical Scenarios

Purpose: To use predictive analytics to perform in-silico experiments with controllable parameters to predict counterfactual malnutrition outcomes. A Bayesian probabilistic approach is used to model best-case and worst-case malnutrition scenarios to theoretically inform policymakers. Counterfactual simulations are used for predictive analytics to analyze the cause of the results. The BN model's predictive efficiency is measured using methods that include the gains curve, the lift curve, reliability, Gini index, lift index, calibration index, the binary log-loss, the correlation coefficient R, the coefficient of determination R2, root mean square error (RSME), and normalized root mean square error (NRSME).

3. Methods

3.1. Dataset of the Malnutrition, Health and Population Variables

For ease of illustrations of key methodological concepts, the data file used in the current paper is a transposed subset (see Table 1) of the World Bank's health, nutrition, and population statistics dataset [38]. The full dataset containing indicators of health, malnutrition, and population statistics was made available to the public domain by the World Bank [10]. The present paper does not attempt to undermine the laudable, analysis-driven predictive studies that were based on other approaches. Instead, it aims to offer a complementary option to promote the use of a multidisciplinary integrative approach to engaging in probabilistic statistical reasoning via AI-Thinking.

Table 1. Code book of the data.

Variable/Node Name
Year
Current health expenditure per capita (current US$)
Immunization: BCG (% of one-year-old children)
Immunization: DPT (% of children ages 12–23 months)
Immunization: HepB3 (% of one-year-old children)
Immunization: measles (% of children ages 12–23 months)
Immunization: Pol3 (% of one-year-old children)
Incidence of malaria (per 1000 population at risk)
Incidence of tuberculosis (per 100,000 people)
Literacy rate: adult total (% of people ages 15 years and above)
Literacy rate: youth total (% of people ages 15–24 years)
Malnutrition prevalence: height for age (% of children under 5 years)
Malnutrition prevalence: weight for age (% of children under 5 years)
Mortality rate: under-5 years (per 1000)
Number of people who are undernourished
People practicing open defecation (% of population)
People using safely managed drinking water services (% of population)
People using safely managed sanitation services (% of population)
Prevalence of anemia among children (% of children under 5 years)
Prevalence of anemia among women of reproductive age (% of women ages 15–49 years)
Prevalence of overweight (% of adults)
Prevalence of overweight (% of children under 5 years)
Prevalence of undernourishment (% of population)
Public spending on education: total (% of GDP)
Rural population growth (annual %)
Unemployment: total (% of total labor force)
Urban population (% of total population)
Urban population growth (annual %)

3.2. Data Analysis Methodology

3.2.1. Rationale for Using the AI-Based Bayesian Network Approach

Malnutrition and public healthcare researchers, such as Hayat and Abian [39] and Neill [40] have utilized AI in their studies. However, the AI techniques outlined in those studies might be too technically difficult for analysts and stakeholders who may not be trained in artificial intelligence or computer science to understand. Nevertheless, there is another easier AI-based approach. The AI-based BN method [41] for interpreting statistical data is one of the many methods in AI-related research which has gained traction in recent years [42]. The BN approach [25–27] is ideal for the study of non-parametric data because it does not need a standard parametric distribution in the underlying parameters of a model [43–45]. The Bayesian paradigm enables practitioners to perform computational simulations by including prior knowledge into the analyses. As a consequence, multiple rounds of null hypothesis testing are not needed using Bayesian computational analysis methods [46–48]. This is crucial as there might not be large datasets that are related to malnutrition.

Researchers such as Kaplan [49], Levy [50], Mathys [51], and Muthén and Asparouhov [52], Bekele and McPherson [53], and Millán, Agosta, and Cruz [54] have also utilized the Bayesian approach because it enables them to measure mutual information, as depicted in Claude Shannon's Information Theory [55], which calculates the probabilistic amount of commonality between two data distributions that may not be parametric. BN can also be used to forecast "Black Swan" scenarios [56], so-called for unusual and unpredictable worst-case scenarios, and for analysis of failures in systems [57]. In this paper, BN is used to predict the best-case scenario and the worst-case Black Swan scenario which can adversely affect malnutrition levels. This type of predictive analytics can be particularly valuable in informing stakeholders, such as policy makers and researchers concerned with malnutrition-related issues in ever-changing conditions rife with uncertainty [58].

3.2.2. *The Bayesian Theorem*

A brief introduction to the Bayesian theorem and BN will be presented here. It can never, however, do justice to the well established BN corpus. Readers interested in learning more about BN are encouraged to peruse the works of Cowell, Dawid, Lauritzen, and Spiegelhalter [59]; Jensen [60]; and Korb and Nicholson [61].

The mathematical formula (see Equation (1)), on which BN was based, was developed by the mathematician and theologian Reverend Thomas Bayes and posthumously published in 1763 [41].

$$P(H|E) = \frac{P(E|H).P(H)}{P(E)} \tag{1}$$

According to Equation (1), H represents a hypothesis and E represents a piece of evidence. $P(H|E)$ is referred to as the conditional probability of the hypothesis H, which is the likelihood of H occurring given the condition that the evidence E is true. It is also referred to as the posterior probability, which is the probability of the hypothesis H being true after calculating how the evidence E influences the verity of the hypothesis H.

$P(H)$ and $P(E)$ represent the probabilities of the likelihood of the hypothesis H being true, and of the likelihood of the evidence E being true, independent of each other, and is referred to as the prior or marginal probability—$P(H)$ and $P(E)$, respectively. $P(E|H)$ represents the conditional probability of the evidence E, that is, the likelihood of E being true, given the condition that the hypothesis H is true. The quotient $P(E|H)/P(E)$ represents the support which the evidence E provides for the hypothesis H.

3.3. *Software Used: Bayesialab*

The software that will be used is Bayesialab [62]. A highly recommended pre-requisite activity which would be beneficial to the reader is to download and read the free Bayesialab user guide fom its website before continuing with the following examples as outlined in the following sections. It includes the details of the Bayesialab software's various methods and functionalities that are too lengthy to be included in the current paper.

3.4. *Pre-Processing: Checking for Missing Values or Errors in the Data*

This section presents the procedures in the descriptive analysis that are used to explain "What has already happened?" in the collected dataset. The dataset comprising 19 rows of data in a dataset containing indicators from the year 2000 until 2018 about malnutrition, health, and population statistics was imported into Bayesialab. The purpose was to discover the informational motif of the data [63].

The first step was to check the data for any anomalies or missing values before using Bayesialab to build the BN. There were no irregularities in the dataset used in this analysis. Should other researchers find missing values in their datasets, however, the researchers could use Bayesialab to estimate and fill in the missing values instead of discarding the data row with a missing value. By machine-learning the overall structural characteristics of the whole data set being analyzed, Bayesialab would be able to predict the missing values. Bayesialab uses the Structural EM algorithms and Dynamic Imputation algorithms to predict any missing values [64]. There were 61 missing values (11.47% of the data) and they were predictively addressed by Bayesialab. Discretization of the continuous data in multiple columns could be automatically performed by the Bayesialab software [65]. The R2-GenOpt algorithm used was the optimal approach Bayesialab suggested. It was a genetic discretization algorithm to maximize the R2 coefficient of determination between each discretized variable and its corresponding continuous variable [66].

3.5. Overview of the BN Approach Used to Machine-Learn the Data

A brief description of the nomenclature used to characterize the BN structure is given here before presenting the results of the machine learning process performed by the BN model. Nodes (the round cornered rectangles showing the data distribution histograms) represent variables of interest. Such nodes may represent symbolic/categorical variables, numerical variables with discrete values, or discretized continuous variables. While BN can handle continuous variables, in the current paper, we exclusively address BN with discrete nodes, as it is more important to heuristically categorize variables into high, mid, and low levels so that discussions among stakeholders would be easier to facilitate.

Directed links (arrows) between variables could represent information (statistical) or causal dependence. Directions are used to define relationships. For example, in a Bayesian network with a link from X to Y, X is the parent node of Y, and Y is the child node. However, it is important to note in the current paper that the presented Bayesian network is the machine-learned result of probabilistic structural equation modeling (PSEM). It is not a causal model diagram and therefore, the arrows do not represent causation. They merely represent probabilistic structural relationships between the parent node and the child nodes.

Bayesian Networks, also known as Belief Networks, Causal Probabilistic Networks, and Probabilistic Influence Diagrams, are graphical models consisting of nodes (variables) and arcs or arrows. Each node contains the respective variable data distribution. Each arc or arrow between the nodes indicates the probability of the strength of the relationship between the variables [67].

Using BN, it becomes possible to use descriptive analytics to analyze the relations between the nodes (variables) and the manner (the motif or pattern) in which initial probabilities, such as the proportions of the various input variables from health or population statistics might influence the probabilities of future outcomes in the malnutrition levels.

In addition, given the final outcome, BN can also be used to perform counterfactual speculations on the initial data distribution status in the nodes (variables). To explain how counterfactual simulations can be applied using BN, examples will be provided in the predictive analytics segments in the context of the current paper. For example, if we wish to find out the conditions of the initial states in the nodes (variables) which would lead to high probability of attaining low-level malnutrition, we can simulate these hypothetical scenarios in the BN.

The relationship between each pair of related nodes (variables) is calculated by their respective Conditional Probability Table (CPT), which is the probability of the strength of the relationship between the parent node's data distribution and the child node's data distribution [68]. Bayesialab automatically machine-learns the values in the CPT based on the data distribution of each column/variable/node in the dataset. However, if the human user wants to bypass the machine learning program, it is possible for the user to manually input the probability values into the CPT.

4. Results

4.1. Descriptive Analytics: A Cursory "First Look"at the Data Using Target-Means Total Effects Analysis

A cursory "first look" at the data can be achieved by visualizing the influence of the variables on the target node in the BN. The Total Effects tool in Bayesialab (see Figure 1) can plot the total effects of the variables in the malnutrition, health, and population statistics on the target node (percentage of the number of people who are undernourished). It suggests that their relationships are curvilinear. Even though some might look almost linear at first glance, they are not perfectly linear. Therefore, it would be difficult to use conventional frequentist-based linear regression correlation methods to calculate the impacts of the variables (which is based on non-parametric and non-linear data) on the target. Here is where BN excels in calculating how curvilinear data from the variables might influence the outcome of the percentage of number of people who are undernourished, because the concept of the Markov Blanket [32], in conjunction with Response Surface Methodology (RSM) [33–36] are utilized for examining the optimization of relations between variables in the computational model. Nevertheless, it is obvious that using this graph to explain how each variable might influence the outcome could still be un-intuitive because it is hard to express the analysis in human-centric probabilistic terms. Therefore, in the next section, a more intuitive probabilistic reasoning approach is presented. The new approach will also take into account the possible relationships between the variables, as it calculates the influences on the target outcome.

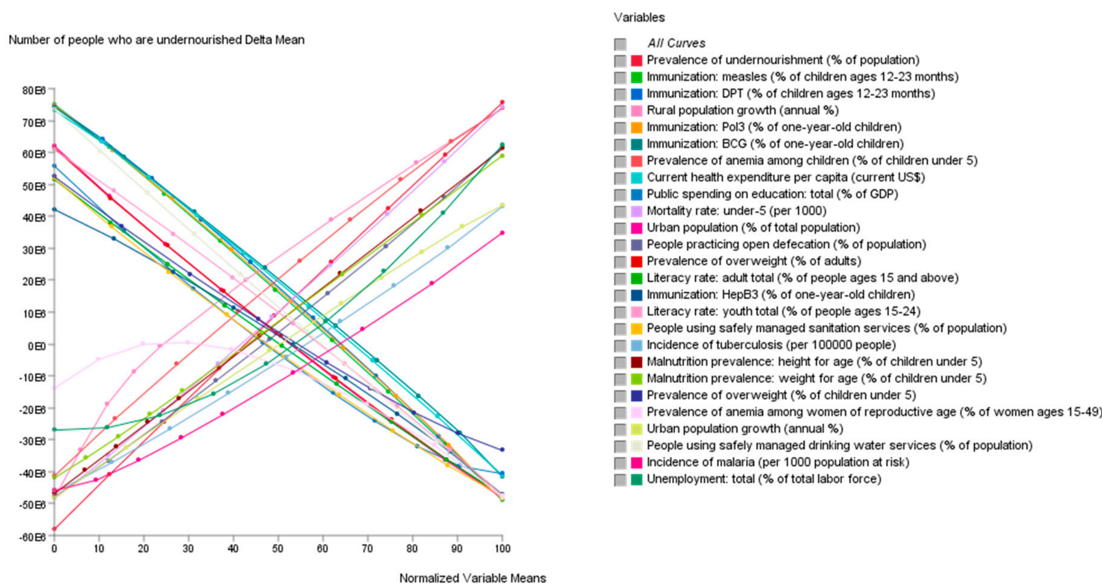

Figure 1. Target-means total effects analysis of how variables might impact the target's outcome.

4.2. A User-Friendly Semi-Supervised Machine Learning Approach

Semi-supervised machine learning is one of the easiest and intuitive ways that can be used by analysts who are not computer scientists to analyze the dataset and generated possible relationships between the variables in the malnutrition, health, and population dataset.

In this section, descriptive analytics can first be performed on the collected data to learn more about the characteristics of its collective pattern or motif. Subsequently, predictive analytics using semi-supervised machine learning will be used to reveal the motif machine learned in this section to generate simulations of the theoretical scenarios in-silico to forecast conditions which we might like to achieve or avoid.

To complement the work of colleagues who might prefer to visualize data of this semi-supervised BN machine-learned model in terms of frequentist statistics, descriptive analytics can also be performed by using the Pearson correlation analysis tool in Bayesialab. It can be used to provide another perspective of looking at the data (see Figure 2). The results of the descriptive analytics are presented in Table 2. Figure 2 shows a diagrammatic visualization of the data.

Table 2. Results of Pearson correlation analysis.

Variable/Node	Low Level		Mid-Level		High Level	
	Range	**Probability**	**Range**	**Probability**	**Range**	**Probability**
Current health expenditure per capita	<580	21.15%	581–788	21.15%	>788	57.71%
Immunization: BCG	<=83.0	26.35%	83.1–87.2	15.88%	>87.2	57.77%
Immunization: DPT	<=74.6	21.12%	74.7–81.3	26.53%	>81.3	52.53%
Immunization: HepB3	<=65.2	32.84%	65.3–76.3	30.29%	>76.3	36.87%
Immunization: Measles	<=75.9	26.35%	76.0–81.1	21.12%	>81.1	52.53%
Immunization: Pol3	<=76.1	26.35%	76.2–82.1	21.12%	>82.1	52.53%
People using safely managed drinking water services	<=62.8	15.89%	62.9–66.5	42.72%	>66.5	41.39%
People using safely managed sanitation services	<=32.7	36.83%	32.8–39.4	32.47%	>39.4	30.70%
People practicing open defecation	<=12.6	36.82%	12.7–17.1	31.59%	>17.1	31.59%
Incidence of malaria	<=61.2	26.64%	61.3–67.7	18.64%	>67.7	56.72%
Incidence of tuberculosis	<=145	30.59%	146–160	27.17%	>160	42.24%
Prevalence of undernourishment	<=11.8	47.28%	11.9–13.8	21.12%	>13.8	31.60%
Number of people who are undernourished	<=822 million	45.46%	823–879 million	17.62%	>879 million	36.82%
Prevalence of anemia among women of reproductive age	<=30.4	38.93%	30.5–31.6	46.24%	>31.6	14.83%
Prevalence of anemia among children	<=42.8	57.74%	42.9–44.6	21.13%	>44.6	21.13%
Prevalence of overweight adult	<=33.1	31.59%	33.2–36.2	31.59%	>36.2	36.82%
Prevalence of overweight children	<=5.1	29.35%	5.1–5.4	42.12%	>5.4	28.53%
Malnutrition prevalence among children: height	<=23.8	24.83%	23.9–26.1	43.69%	>26.1	31.48%
Malnutrition prevalence among children: weight	<=14.6	26.19%	14.7–16.3	42.88%	>16.3	30.93%
Mortality rate of children under age 5	<=49	42.06%	50–63	31.59%	>63	26.35%

The results of the Pearson correlation analysis are interpreted as follows. There is moderate probability (57.71%) of high expenditure on healthcare (i.e. more than US$788.75 per capita).

On immunization uptake, there are moderate probabilities of high coverage of BCG, DPT, measles and Pol3 immunizations:

- 57.77% probability that more than 87.2% of the population has received BCG immunization;
- 52.53% probability that more than 81.3% of the population has received DPT immunization;
- 52.53% probability that more than 81.1% of the population has received measles immunization;
- 52.53% probability that more than 82.1% of the population has received Pol3 immunization.

However, there is no conclusive inference on the immunization uptake of HepB3. There is an almost equal probability of HepB3 immunization coverage at the low, mid and high levels.

On the usage of safely managed drinking water services, there is a combined high probability of 84% (that is, 42.72% + 41.39%) that >62.8% of the population is using. However, there is no conclusive inference on the usage of safely managed sanitation services and the practice of open defecation. There is an almost equal probability of people using safely managed sanitation services and people practicing open defecation at the low, mid and high levels.

The results on disease incidences indicate that there is moderate probability (56.72%) of high incidence of malaria (i.e., more than 67.7 out of every 1000 people) as well as moderate probability (42.24%) of high incidence of tuberculosis (i.e., more than 160 out of every 100,000 people).

Among the general population, there is 47.28% probability of low prevalence of undernourishment (i.e., less than 11.8% of the population) and 45.46% probability of a small population of undernourished people (i.e., fewer than 822 million people). The prevalence of anemia among women of reproductive age (15–49 years old) is likely to be at the mid-level (i.e., neither too high nor too low) with 46.24% probability. There is an almost equal probability of prevalence of overweight adults at the low, mid and high levels. That is to say that there is no conclusive inference on the prevalence of overweight adults.

The results related to young children under the age of 5 years show a 57.74% probability of low prevalence of anemia (i.e., less than 42.8% of the child population) and 42.06% probability of low mortality rate (i.e., less than 49 per 1000 children). The prevalence of overweight children (42.12% probability), malnutrition in terms of height (43.69% probability) and malnutrition in terms of weight (42.88% probability) were all at the mid-level (i.e., neither too tall nor too short).

In answering RQ1, the dataset is characterized by high levels of health expenditure, high immunization uptakes (BCG, DPT, measles and Pol3) and a high number of people using safely-managed drinking water services, as the occurrences of these characteristics are supported by high probabilities. Descriptive analytics of the dataset also suggest the likelihood of low prevalence of undernourishment, low prevalence of anemia and low mortality rate among young children, but high incidence of malaria and tuberculosis. In addition, anemia among women, malnutrition of children, in terms of height and weight, are likely to be at the mid-levels (i.e., neither too high nor too low).

A number of significant correlations, which may appear intuitive, are identified from Figure 2. The prevalence of undernourishment is positively correlated to the number of under-nourished people (94.84%). The percentage of people using safely managed drinking water services is negatively correlated to the incidence of malaria (86.27%). The percentage of people using safely managed sanitization services is negatively correlated to the incidence of tuberculosis (94.36%). The percentage of population practicing open defecation is negatively correlated to the percentage of people using safely managed drinking water services (92.02%). The prevalence of malnutrition in young children's height is positively correlated to the prevalence of malnutrition in their weight (94.52%). The mortality rate of young children is positively correlated to the growth of the urban population (87.83%). The prevalence of anemia among young children is negatively correlated to health expenditure (92.60%).

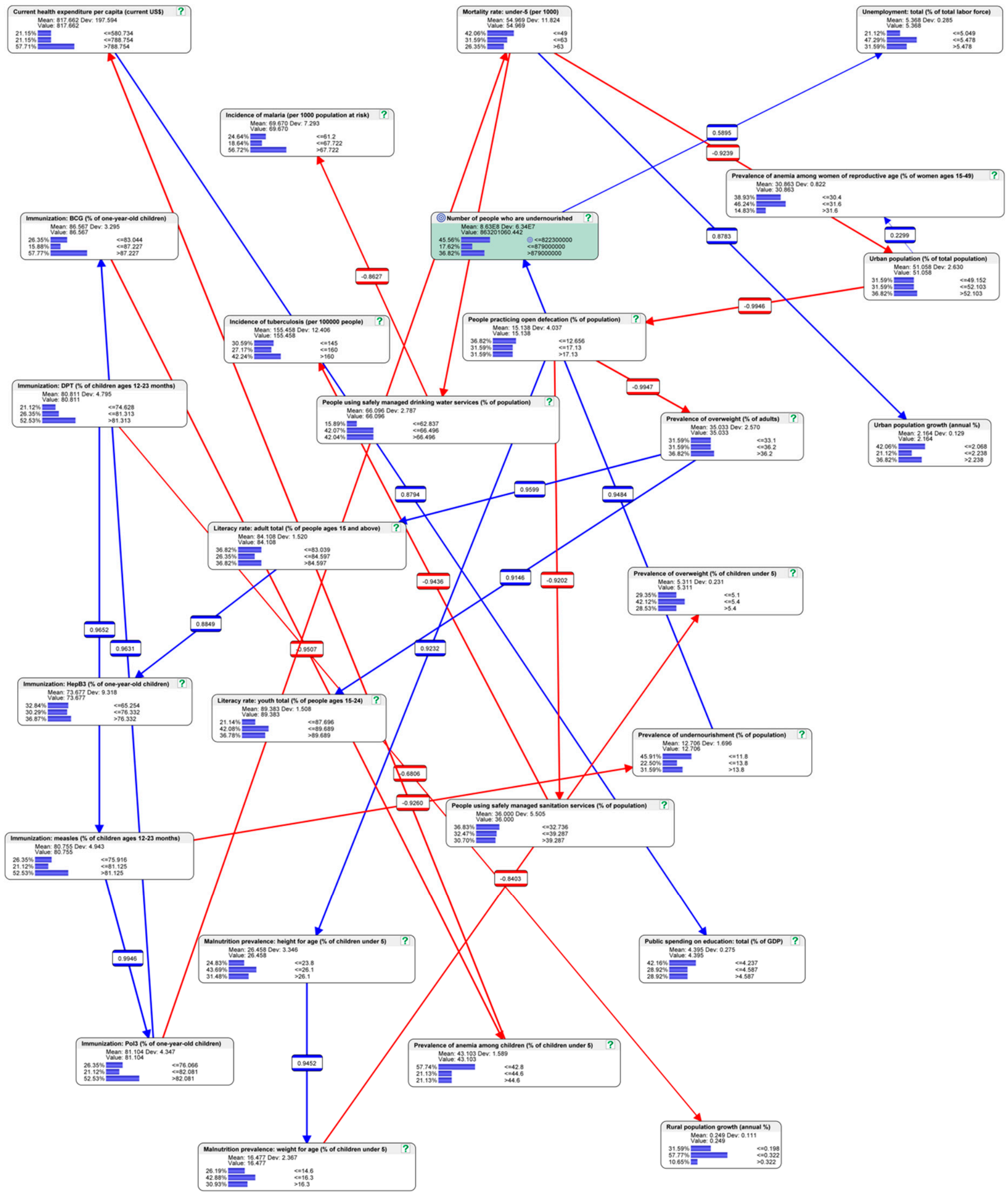

Figure 2. Semi-supervised Machine Learning using Maximum Spanning Tree Bayesian Network: to discover potential relations between variables in the model.

4.3. Predictive Analytics of the Best-Case Scenario

The purpose of these predictive analyses presented here is not to deterministically find the "correct answer" but to propose a more intuitive probabilistic reasoning method for dialog between analysts who may not be computer scientists and the stakeholders. Hopefully, this predictive method would create future opportunities for analysts to use their own sets of data and engage with the vast body of empirical studies on malnutrition analyses in the research literature. Understandably, it would be too extensive in this paper to compare every predictive result to the laudable corpus of malnutrition research in the field. Therefore, this paper will mainly focus on the delineation of the proffered predictive method.

Simulation of Scenario: *What* conditions are needed *if* we wish to achieve the best-case scenario (that is, the "percentage of people who are undernourished" is at the low-level)?

To simulate the conditions for achieving a low level of undernourished population, hard evidence is applied by setting the counterfactual value of 100% (originally 45.46%) on the data bin of low-level (defined as less than 822,300,000 people); 0% is set at the mid-level (between 822,300,000 and 879,000,000 people) compared to the original 17.62%; and 0% is set at the high-level (>879,000,000 people) compared to the original 36.82%.

The corresponding counterfactual results are displayed in Table 3 under the header "Predicted". The up and down arrows next to the predicted value indicate an increase and decrease over the original value respectively. Figure 3 shows a diagrammatic presentation of the results.

Table 3. Results of simulation of best-case scenario.

Variable/Node	Low Level		Mid-Level		High Level	
	Original	Predicted	Original	Predicted	Original	Predicted
Current health expenditure per capita	21.15%	0.64% ↓	21.15%	1.76% ↓	57.71%	97.60% ↑
Immunization: BCG	26.35%	0.46% ↓	15.88%	1.42% ↓	57.77%	98.12% ↑
Immunization: DPT	21.12%	0.30% ↓	26.35%	1.80% ↓	52.53%	97.90% ↑
Immunization: HepB3	32.84%	11.57% ↓	30.29%	20.77% ↓	52.53%	67.66% ↑
Immunization: measles	26.35%	0.24% ↓	21.12%	1.66% ↓	52.53%	98.11% ↑
Immunization: Pol3	26.35%	0.35% ↓	21.12%	1.76% ↓	52.53%	97.90% ↑
People using safely managed drinking water services	15.89%	0.44% ↓	42.72%	21.60% ↓	41.39%	77.96% ↑
People using safely managed sanitation services	36.83%	9.03% ↓	32.47%	21.60% ↓	30.70%	56.63% ↑
People practicing open defecation	36.82%	68.11% ↑	31.59%	27.60% ↓	31.59%	4.29% ↓
Incidence of malaria	26.64%	44.70% ↑	18.64%	33.61% ↑	56.72%	21.69% ↓
Incidence of tuberculosis	30.59%	55.71% ↑	27.17%	29.28% ↑	42.24%	15.02% ↓
Prevalence of undernourishment	47.28%	97.72% ↑	21.12%	2.16% ↓	31.60%	0.13% ↓
Prevalence of overweight adults	31.59%	4.43% ↓	31.59%	27.62% ↓	36.82%	67.95% ↑
Prevalence of anemia among women	38.93%	41.21% ↑	46.24%	31.46% ↓	14.83%	27.33% ↑
Prevalence of anemia among young children	57.74%	97.88% ↑	21.13%	1.62% ↓	21.13%	0.49% ↓
Mortality rate of young children	42.06%	78.17% ↑	31.59%	21.37% ↓	26.35%	0.46% ↓
Malnutrition prevalence among children: height	24.83%	45.45% ↑	43.69%	50.03% ↑	31.48%	4.52% ↓
Malnutrition prevalence among children: weight	26.19%	45.40% ↑	42.88%	49.25% ↑	30.93%	5.35% ↓
Prevalence of overweight children	29.35%	7.72% ↓	42.12%	47.38% ↑	28.53%	44.90% ↑

The results of the counterfactual best-case scenario are interpreted as follows. The public healthcare expenditure per capita is predicted to be high, due to very high probabilities at the high-level (97.60%), and very low probabilities at the low-level (0.64%) and mid-level (1.76%). The prevalence of undernourishment is less likely under the best-case scenario, as shown by the very high probability (97.72%) of low occurrences.

The coverage of BCG, DPT, measles and Pol3 immunization is predicted to increase significantly under the best-case scenario, as shown by the very high probabilities (98.12%, 97.90%, 98.11%, 97.90% respectively) at the high level (defined as >87% coverage of BCG and >82% of Pol3 of the one-year old population; and >81% coverage of DPT and measles of the toddler population aged 12–23 months). As for HepB3, the predicted coverage is lower (67% probability of >76% of one-year old population) and the predicted increase is smaller, compared to the other four immunizations.

The usage of safely managed drinking water services and sanitation services is predicted to increase (77.96% and 56.63% probability of occurrences at the high-level respectively, used by >66%

and >39% of population respectively). The practice of open defecation is predicted to drop mostly to the low-level (68.11% probability of occurrences at the low-level <=12% of the population).

The incidences of malaria and tuberculosis are expected to decrease, as there are higher probabilities of occurrence at the low-level (44.70% and 55.71% respectively) and mid-level (33.61% and 29.28% respectively), and lower probability of occurrence at the high-level (21.69% and 15.02% respectively).

There is likely an increase in the prevalence of overweight adults (67.95% probability) in the high level (defined as more than 36% of the population). This suggests that with less undernourishment (as the target), there might be a possibility of increase in the prevalence of overweight adults. Here is an opportunity where the notion of AI-Thinking could be useful for asking more questions to gain deeper insights. This simulated scenario might seem counter-intuitive at first; however, it might be an area of interest for further discussions between the analysts and the policy makers, as malnutrition could also refer to the malfunction or imbalance of nutrition.

The projected increase in the prevalence of anemia among women of reproductive age (15–49 years old) was due to a higher probability (27.33% compared to the original 14.83%) of occurrence in the high levels (defined as more than 31.6% of the female population). This hypothetical scenario might seem counter-intuitive at first, however, it might be an area of interest for further discussion by the analysts and policy makers, as malnutrition could also refer to the malfunction or imbalance of nutrition and not just conditions influenced by undernourishment. This is an example of an opportunity where AI-Thinking could assist the nutrition analyst in asking further human-centric questions via meaningful discursive discussions with other experts.

The mortality rate and the prevalence of anemia among young children are expected to drop as indicated by the very low probability (0.46%) of mortality at the high-level (defined as more than 63% of the children population) and the very low probability (0.49%) of anemia occurrences at the high level (defined as more than 45% of the children population).

The prevalence of malnutrition in terms of height and weight for children under the age of 5 years are predicted to be mostly at the low-level (50.03% and 45.40% probability for height and weight respectively) and at the mid-level (45.45% and 49.25% probability for height and weight respectively). However, the prevalence of overweight young children (under 5 years) is predicted to increase, from 28.53% to 44.90% probability of occurrences at the high-level (>5.4% of the children population). This suggests that with less undernourishment (as the target), there might be a possibility of a slight increase in the prevalence of overweight children. This hypothetical scenario might seem counter-intuitive at first, however, it might be an area of interest for further discussion by the analysts and policy makers, as malnutrition could also refer to the malfunction or imbalance of nutrition.

In answering RQ2, the simulated best-case scenario would depict a situation where the expenditure on public healthcare would significantly increase, and the the prevalence of under-nourished population would diminish significantly. Immunization coverage would increase significantly, and public hygiene would improve moderately (in terms of water and sanitization service usage and open defecation in public). In addition, the incidences of diseases (malaria and tuberculosis) and the prevalence of children malnutrition are expected to drop moderately, while that of anemia and mortality would fall more significantly. Here is an opportunity for AI-Thinking to be educed in analysts by engaging with other research in the literature, for example, by perusing the works of malnutrition experts such as Rodríguez et al. [69], Asim and Nawaz [70], and Alkhaldy [71].

However, there are some unexpected counterfactual results from the simulation. There was an increase in the prevalence of overweight adults and young children, as well as anemia among women. This calls for deeper analysis. Here is another opportunity for AI-Thinking to be educed by conversing with other empirical studies, such as those by malnutrition and obesity researchers Troesch et al. [72], and Shahid and Bishop [73], and by malnutrition and anemia experts such as Wieringa et al. [74].

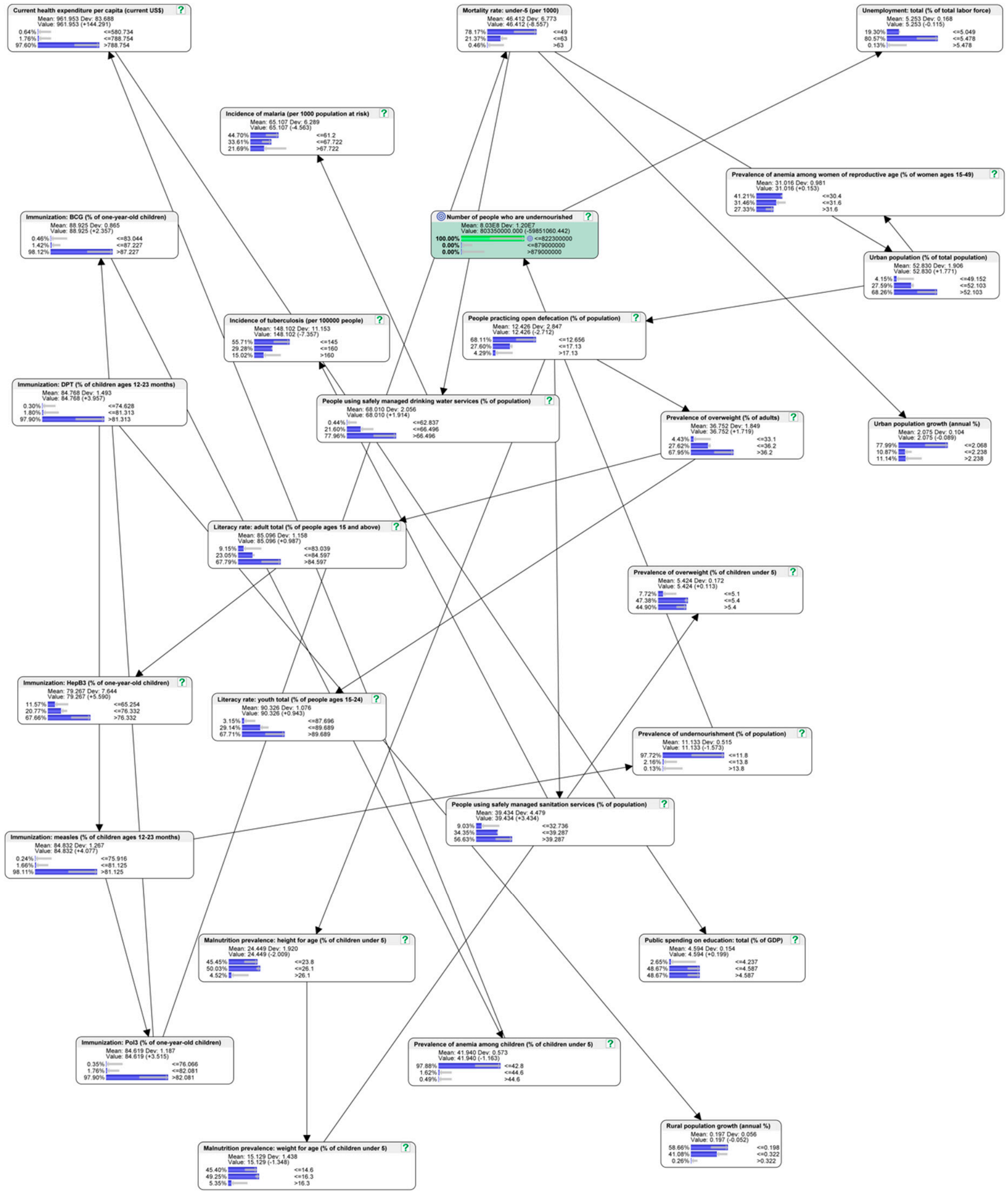

Figure 3. Semi-supervised Machine Learning: counterfactual prediction of best-case scenario conditions needed in direct and/or integrative interventions to achieve low number of people who are undernourished.

4.4. Predictive Analytics of the Worst-Case Scenario

Simulation of Scenario: What conditions would contribute to the worst-case scenario of having high malnutrition as an outcome?

To simulate the conditions for the outcome of high-level of undernourished population, hard evidence is applied by setting the counterfactual value of 100% on the data bin of >879,000,000 people. The corresponding counterfactual results (see Figure 4) of the conditions needed to observe a high-level of undernourished people are presented in Table 4.

Table 4. Results of simulation of worse-case scenario.

Variable/Node	Low Level		Mid-Level		High Level	
	Original	**Predicted**	**Original**	**Predicted**	**Original**	**Predicted**
Current health expenditure per capita	21.15%	56.06% ↑	21.15%	32.42% ↑	57.71%	11.53% ↓
Immunization: BCG	26.35%	70.54% ↑	15.88%	18.39% ↑	57.77%	11.07% ↓
Immunization: DPT	21.12%	56.67% ↑	26.35%	38.53% ↑	52.53%	4.80% ↓
Immunization: HepB3	32.84%	61.50% ↑	30.29%	34.02% ↑	36.87%	4.48% ↓
Immunization: measles	26.35%	71.02% ↑	21.12%	24.40% ↑	52.53%	4.58% ↓
Immunization: Pol3	26.35%	70.78% ↑	21.12%	24.42% ↑	52.53%	4.80% ↓
People using safely managed drinking water services	15.89%	42.25% ↑	42.72%	53.50% ↑	41.39%	4.24% ↓
People using safely managed sanitation services	36.83%	77.66% ↑	32.47%	18.92% ↓	30.70%	3.42% ↓
People practicing open defecation	36.82%	3.91% ↓	31.59%	21.83% ↓	31.59%	74.26% ↑
Incidence of malaria	26.64%	3.53% ↓	18.64%	2.90% ↓	56.72%	93.58% ↑
Incidence of tuberculosis	30.59%	3.90% ↓	27.17%	15.58% ↓	42.24%	80.52% ↑
Prevalence of undernourishment	47.28%	0.16% ↓	21.12%	14.38% ↓	31.60%	85.46% ↑
Prevalence of overweight adults	31.59%	74.04% ↑	31.59%	21.89% ↓	36.82%	4.07% ↓
Prevalence of anemia among women	38.93%	22.58% ↓	46.24%	75.75% ↑	14.83%	1.67% ↓
Prevalence of anemia among young children	57.74%	11.26% ↓	21.13%	32.44% ↑	21.13%.	56.29% ↑
Mortality rate of young children	42.06%	4.05% ↓	31.59%	25.41% ↓	26.35%	70.54% ↑
Malnutrition prevalence among children: height	24.83%	3.12% ↓	43.69%	23.30% ↓	31.48%	73.58% ↑
Malnutrition prevalence among children: weight	26.19%	5.44% ↓	42.88%	23.75% ↓	30.93%	70.81% ↑
Prevalence of overweight children	29.35%	62.95% ↑	42.12%	26.71% ↓	28.53%	10.35% ↓

The results of the counterfactual worst-case scenario are interpreted as follows. The health expenditure is predicted to decrease significantly (from 57.71% to 11.53% probability of spending at the high level, defined as >US$788 per capita). There would be a high probability (85.46%) of undernourishment people with occurrences of >13.8% of the population.

The immunization coverages for BCG, DPT, HepB3, measles, Pol3 are unlikely (11.07%, 4.80%, 4.48%, 4.58% and 4.80% probability respectively) to be at high levels. It is also highly unlikely (4.24% and 3.42% probability) that >66% and >39% of the population would use safely managed drinking water services and sanitization services respectively. On the other hand, it is more likely (74.26%) that open defecation would be practiced by >17% of the population.

The incidence of malaria and tuberculosis is very likely (93.58% and 80.52% probability respectively) to be at the high level (defined as >67 % and of the population and >160 people out of every 1,000,000 respectively).

The prevalence of anemia among women of reproductive age is predicted to decrease (from 14.83% to 1.67% probability of occurrence at the high level, that is, >31.6% of the women population). This hypothetical scenario might seem counter-intuitive at first; however, it might be an area of interest for further discussion by the analysts and policy makers, as malnutrition could also refer to the malfunction or imbalance of nutrition. This is where the notion of AI-Thinking could play a role.

On obesity, the results show that it is highly likely (74.04% and 62.95%) that there is a low prevalence of overweight adults (<33% of the population) and children (< 5% of the population). This is another area where further analysis may be necessary as the results appeared to be counter intuitive. This is another opportunity where AI-Thinking could contribute to their discourse.

The mortality rate of young children is predicted to increase significantly (from 26.35% to 70.54% probability of occurrences at the high-level defined as >63 per 1000 children). Malnutrition in terms of height and weight are very likely (73.58% and 70.81% respectively) to be high (>26% and >16% of the children population respectively). Similarly, the prevalence of anemia among young children increases (21.13% to 56.29%) at the high level (>45% of the children population under the age of 5 years).

In answering RQ3, the simulated worst-case scenario was the exact opposite of the best-case scenario. The worst outcomes included low immunization coverages, low usage of water and sanitization services, high incidence of malaria and tuberculosis, high mortality of children, and high prevalence of childhood anemia. Similarly, the results that were unexpected of a worst-case scenario—a decrease in overweight adults and young children as well as anemia among women—were from the same variables as that of the best-case scenario. Here is another opportunity for AI-Thinking to be educed by asking further questions and conversing with the research literature. For instance, if one speculates that special circumstances might be affecting malnutrition, it would be insightful to peruse the works of Dureab et al. [75], Volkert et al. [76], and Moramarco et al. [77].

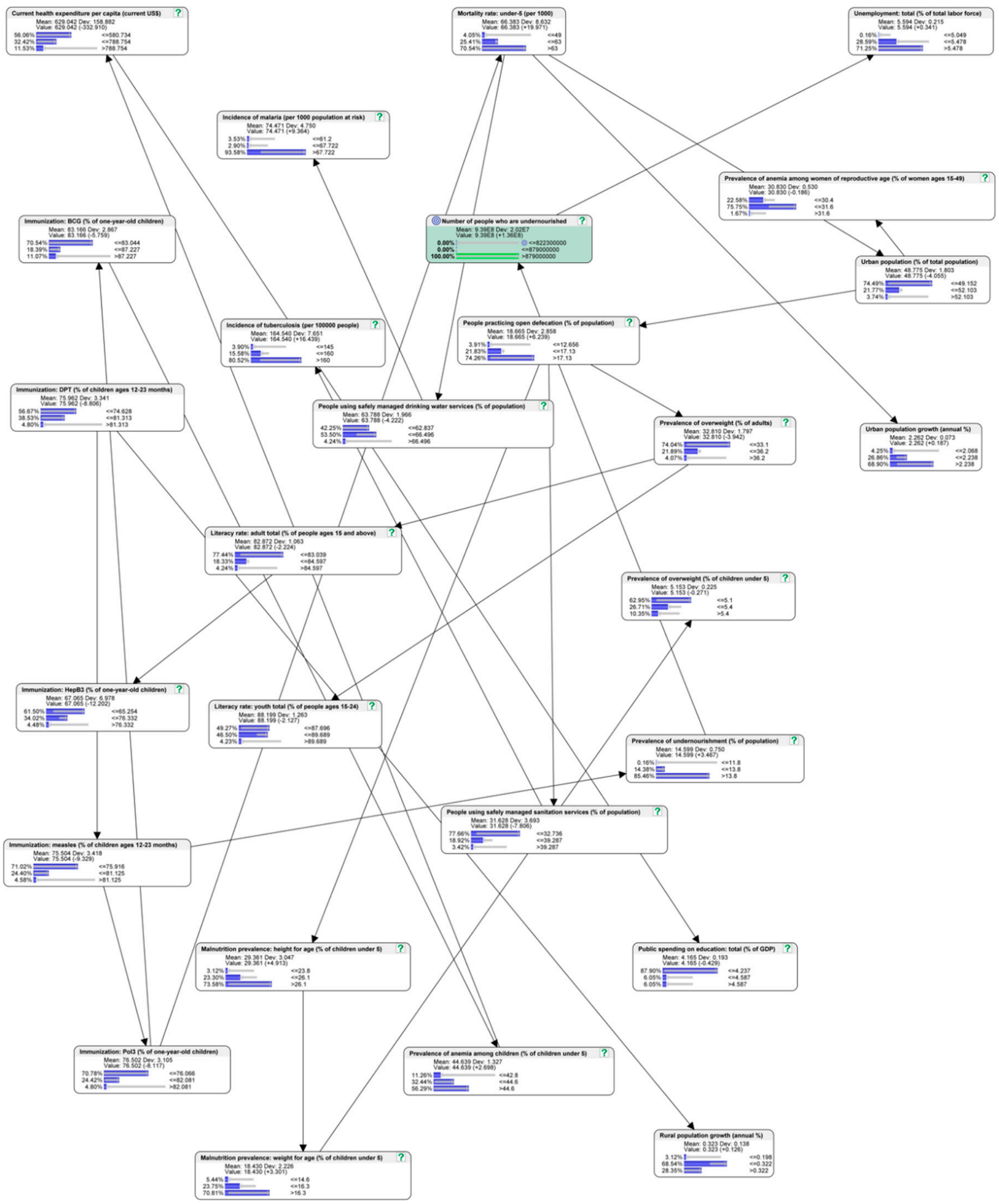

Figure 4. Semi-supervised machine learning: counterfactual prediction of the worst-case scenario conditions to avoid.

4.5. Evaluation of the Predictive Performance of the Bayesian Network Model

4.5.1. Evaluation of the Predictive Performance Using Target Evaluation Cross-Validation by K-Folds

As observed in Bayesialab after performing target evaluation cross-validation by K-Folds on the data distribution of each node in the BN by using the Semi-Supervised algorithm, the Overall Precision was 100%; the Mean Precision was 100%; the Overall Reliability was 95.0617%; the Mean Reliability was 96.2963%; the Gini Index was 57.2368%; the Relative Gini Index was 98.8636%; the Lift Index was 1.8299; the Relative Lift Index was 100%; the ROC Index was 100%; the Calibration Index was 55.0720%; the Binary Log-Loss was 0.0873; the Correlation Coefficient R was 0.9522; the Coefficient of Determination R2 was 0.9066; the Root Mean Square Error (RMSE) was 19,598,315.3716; and the Normalized Root Mean Square Error (NRSME) was 11.0103%.

A confusion matrix (for cross-validating the data by K-Fold in every node) can provide additional information about the computational model's predictive performance. The leftmost column in the matrix contained the predicted values, while the actual values in the data were presented in the top row. Three confusion matrix views would be available by clicking on the corresponding tabs. The Occurrences Matrix (see Figure 5) would indicate the number of cases for each combination of predicted versus actual values. The diagonal shows the number of true positives.

Occurrences | Reliability | Precision

Value	<=822300000 (8)	<=879000000 (3)	>879000000 (7)
<=822300000 (9)	8	0	0
<=879000000 (3)	0	3	0
>879000000 (7)	0	0	7

Figure 5. Evaluation of predictive performance of BN: Occurrences Confusion Matrix.

The Reliability Matrix (see Figure 6) would indicate the probability of the reliability of the prediction of a state in each cell. Reliability measures the overall consistency of a prediction. A prediction could be considered as highly reliable if the computational model produces similar results under consistent conditions.

Occurrences | Reliability | Precision

Value	<=822300000 (8)	<=879000000 (3)	>879000000 (7)
<=822300000 (9)	88.8889%	0.0000%	0.0000%
<=879000000 (3)	0.0000%	100.0000%	0.0000%
>879000000 (7)	0.0000%	0.0000%	100.0000%

Figure 6. Evaluation of predictive performance of BN: Reliability Confusion Matrix.

The Precision Matrix (see Figure 7) would indicate the probability of the precision of the prediction of a state in each cell. Precision is the measure of the overall accuracy which the computational model can predict correctly.

Occurrences | Reliability | Precision

Value	<=822300000 (8)	<=879000000 (3)	>879000000 (7)
<=822300000 (9)	100.0000%	0.0000%	0.0000%
<=879000000 (3)	0.0000%	100.0000%	0.0000%
>879000000 (7)	0.0000%	0.0000%	100.0000%

Figure 7. Evaluation of predictive performance of BN: Precision Confusion Matrix.

The predictive performance of a model can be evaluated using measurement tools such as the Gains curve, Lift curve, cross-validation by K-Fold. In Bayesialab, these tools can be accessed in the "network performance" menu.

4.5.2. Evaluation of the Predictive Performance Using the Gains Curve, Lift Curve and ROC Curve

In the gains curve (see Figure 8), around 42% of the attributes were predicted to be most impactful towards low-level category in the node "% of number of people who are undernourished (<=822300000)". The blue diagonal line represented the gains curve of a pure random policy, which was prediction without this predictive model. The red lines represented the gain curve using this predictive model. The Gini index of 59.26% and relative Gini index of 98.86% suggested that the gains of using this predictive model vis-à-vis not using it, was acceptable.

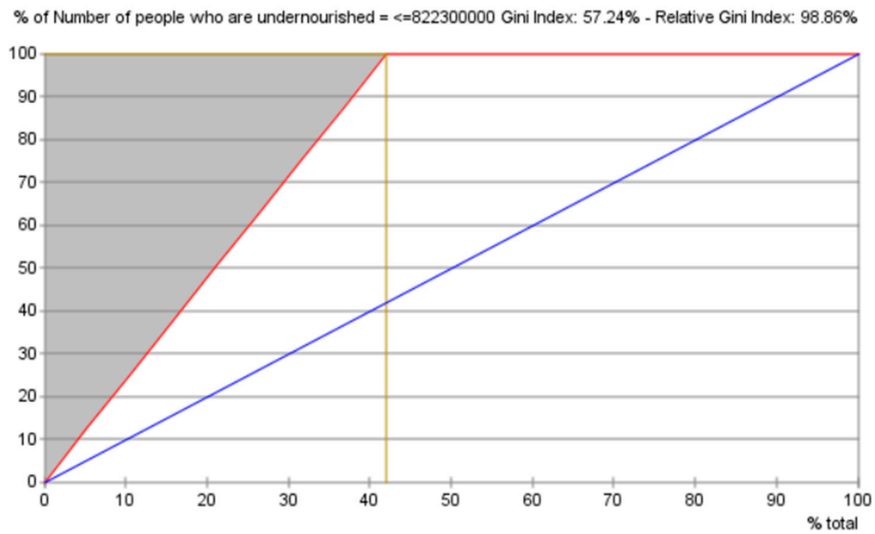

Figure 8. Gains curve.

The Lift curve (see Figure 9) was generated from the results of the previous Gains curve. The value of the best lift around 2.38, was interpreted as the ratio between 100% and 42% (optimal policy divided by random policy). The lift index of 1.8299 and relative lift index of 100% suggested that the performance of this predictive model was acceptably good.

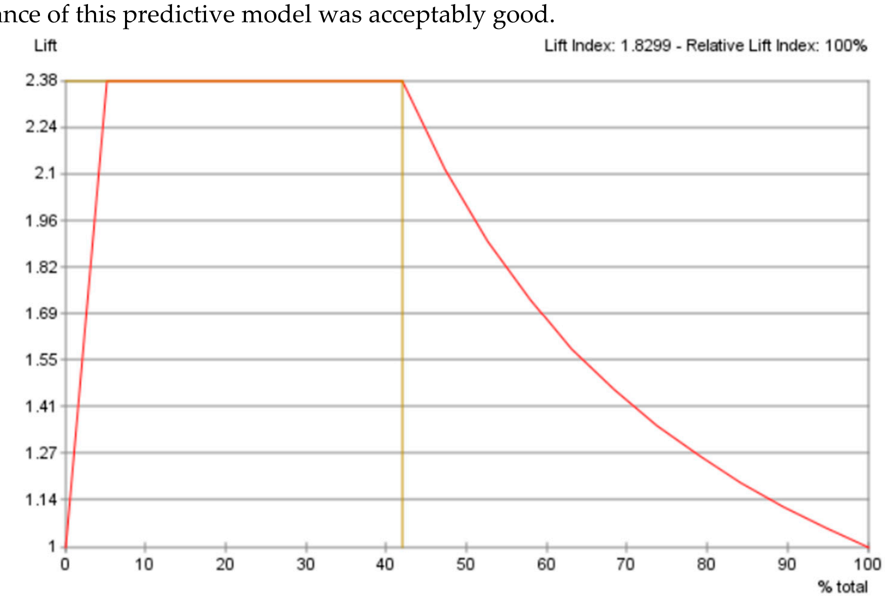

Figure 9. Lift curve.

Together, the Gains curve, and the Lift curve indicated that the predictive performance of the Bayesian network model in the current paper was good.

4.5.3. Limitations of the Study

In this paper, the exploratory character of predictive analytics using BN analysis makes the simulated counterfactual findings suggestive rather than definitive. To keep the publication length manageable, the current paper was only focused on the global system-level view of analyzing the data. It did not drill down into finer-grained analysis at the country level or region level. Only the semi-supervised machine-learning approach was used for illustration purposes. Other forms of machine-learning, such as unsupervised machine-learning were not explored.

In the discretization of continuous variables in the dataset, only the R2-GenOpt algorithm was used. Other algorithms for discretization of continuous data were not explored. For the prediction of missing values in the dataset, only the Structural EM algorithms and Dynamic Imputation algorithms were used in Bayesialab to calculate any missing values. Other forms of algorithms of predicting missing values were not explored.

In addition, the results in this paper only applied to the BN models produced from the current dataset. Thus, when evaluating the potential relationships between variables (nodes) in the BN model, caution must be exercised. As in any simulation analysis, the results depend on the dataset that produced the computational model. Nonetheless, malnutrition analysts should be willing to consider alternative models that could better describe the dataset. In the previous sections, the methods that could be used to assess the predictive performance of BN and the limitations of the study were delineated. Discussions of the study and the conclusion are presented in the next section.

5. Discussion and Conclusion

Although the double burden of malnutrition may pose challenges that are still difficult to surmount, it offers opportunities which could act as catalysts for change. Exploration of the feasibilities of direct and integrative interventions could potentially contribute to informing policy making for the achievement of key global goals. To date, studies using AI to analyze data related to malnutrition, such as those conducted by Hayat and Abian [39], and Neill [40], have required analysts to possess advanced knowledge in AI, mathematics, or computer programming, which might be too technical for laypersons who are not trained in computer science. Malnutrition researchers might have wished that they too, could use AI to generate predictive simulations of alternative counterfactual scenarios. Using the AI-based BN method presented in the current paper in conjunction with the eduction (drawing out) of AI-Thinking for discursive analyses, different scenarios could be simulated to determine the conditions for the best and worst outcomes of global system-level population malnutrition.

On the other hand, the unexpected results that surfaced in the best- and worst-case scenarios—prevalence of overweight adults and young children, as well as anemia among women—could provide opportunities for educing AI-Thinking. This enables analysts and stakeholders who may not be computer scientists to ask further questions based on the outcomes predicted by the AI software.

Silapachote and Srisuphab [78] observed that AI-Thinking can strengthen the thinking practices of an individual by expanding and increasing the use of logical inference, problem-solving heuristics, and data analysis. With the usage of user-friendly of software such as Bayesialab [62] suggested in this paper, or other BN software such as GeNie by BayesFusion [79], or Netica by Norsys [80], or Bayes Server [81], malnutrition analysts may adapt these examples for other studies using their own regional, national, or world-level data.

The current paper contributes significantly to the literature by proposing a way to democratize AI use for malnutrition analysts and stakeholders. Using a user-friendly Bayesian network analysis software and an intuitive human-centric probabilistic reasoning approach, malnutrition analysts, researchers and policy makers—not just computer scientists—can also use AI and XAI to create predictive models from malnutrition, health, and population data. With this approach, individual variables could be kept constant while others might be modified in the computational models to visualize “what-if” scenarios to predict the conditions for optimizing the results and to forecast “at-risk” conditions for preventing unwanted outcomes. Thus, policy makers can potentially be better informed and take pre-emptive measures to prevent the worst-case scenario from happening.

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