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A Promising Technique of Artificial Intelligence for Revisiting the Nexus between Health-Education Disparities and Income Inequality for Developing Economies

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There is an ongoing debate as to whether health and education are negatively affected by income inequality within a society. This issue has received abundant research interest in several disciplines. Income disparities have widened in various developed and developing countries during the process of economic globalization. The idea that inequality causes poor health and education originates from a frequently noted negative association between different income inequality measures and the average health and education status. From the existing literature we know that such aggregate associations might stem from a nonlinear relationship between income and individual health, making it vital to use individual or household level data. Such data enable the separation between different theoretical hypotheses, all consistent with negative aggregate association of inequality both with health and education. Empirical studies using individual level data have produced largely contradictory conclusions. Consistent evidence of a negative association between income inequality and individual health and income inequality and education status are found in the United States and in other developed countries. In contrast, data from other developed countries often find no such correlation, suggesting that a general association between inequality and health does not exist.

Finding the relationship of income inequality with health as well as education in low-income countries is a major unsolved issue and provokes the motivation to find out some promising solutions using some alternative new artifact. Again, owing to the opposite swing of the same circle, disparities exist within education and healths in poor countries are also somewhat extents responsible for sustained income inequality. Therefore, two questions still remain unanswered? One, do disparities inherent in education and health reflect possible explanations of income inequality in developing nations? If yes, then the second question comes into the act, that is, how shall we measure inequalities exist in education and health and what are the components of both

health and education that should be included to get a robust measure? These issues motivated us to take this as a research exercise.

To perform the said exercise empirically, several alternative techniques have been suggested to define indices for both health and education, and to relate the same with the index of income inequality. However, among all the alternatives, the Artificial Neural Networks (ANN) has been given emphasis for this said study. It is a widely accepted versatile approach of applied Artificial Intelligence. Though, ANNs were developed in the sixties as devices for classification and regression, but still now they are gaining their importance and wide acceptance in multiple domains. Presently, the ANNs provide powerful models for statistical data analysis by generating efficient and consistent estimators. In fact, Multiple linear regression models are also very powerful technique in order to estimate the linear relationship but not at all suitable for applications where the inherent nonlinear functional relationship is a major issue. But in a realistic social science scenario, the assumption of linearity is seldom to be satisfied. Fortunately, the ANN may be a graceful alternative to handle any hidden nonlinearity in social science data.

Advancing over traditional ANNs, a Back-propagation Neural Network (BPNN) is one of the best-performed variants for the random dataset and guided by some criterion such as error convergence, optimized number of iterations or minimal errors.

For the present study, two contributory indices have been introduced: Health Inequality Index (hi) and Education Inequality Index (ei). The values of these two indices are obtained from the health inequality parameters and education inequality parameters respectively. Two three-layered (input layer, hidden layer and output layer) BPNNs are designed to calculate these two indices. The hidden layer is designed for better handling the nonlinearity present in the domain of study. For best performance, the hidden layer of each network is designed with ten neurons using an optimization method. The first BPNN is designed to estimate the values of hi and the second one is for ei respectively. The first BPNN considers four health parameters (Domestic general government health expenditure per capita, Domestic private health expenditure per capita, Life expectancy and Infant mortality rate) based on status and investment criterion as inputs through four input neurons and generates the values of hi as the output. Similarly, the input layer of the second BPNN consists of three neurons for three education parameters (Government expenditure on education, Primary school enrollment and Secondary school enrollment) based on status and investment criterion as inputs through three input neurons and generates the values of ei as the output. Both the networks are trained with a learning rate of 0.5 with 200 epochs.

As a first phase of the experiment, these two systems have been trained and tested with the available data (World Development Indicators) of some selected developing countries for a period of 15 years (1995 to 2010). The input data are normalized between zero and one by using a standard statistical technique to avoid possible numeric overrun and scalar heterogeneity among input variables. Further, GINI (GI) index is used (Standardized World Income Inequality

Database) to compare and relate the heterogeneity exist between our estimated indices and GI in developing countries.

The proposed ANN based model significantly mined two novel observations: First of all, disparities exist in health, education, and income inequalities are not heterogeneous at all rather homogenous in nature. It clearly dictates that education and health inequalities can efficiently explain the inherent characteristics of income inequality, at least in developing areas. Policymakers can use education and health inequalities as a proxy of income inequality in labour rich countries.

Secondly, a rank can be assigned to each nation to compare its position corresponding to the stylized ranking table based on the indices mentioned above. The ranking table gives us a clear view to understand the inherent features of sustained income disparity or social disparity in developing nations. Such policy-oriented outcomes may help policymakers to choose best possible measure education optimization, health care improvement or growth and poverty alleviation.