# The Linkages between Mortality, Education and Prosperity Using Partially Latent Models: A Hierarchical Approach

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## Abstract

***Background****: Many studies had been carried out to examine the association between mortality, education and prosperity. The purpose of this study is to examine the relationship between three indicators of education: the percentages of population who achieved primary, secondary and tertiary education; prosperity factor which includes three indicators: the percentages of CLASS1, CLASS2 and CLASS3 of occupation; and mortality factor which also includes three indicators: standardized (infant, neonatal and stillbirth) mortality ratios using partially latent models. The data were collected from the information of 81 districts based on the census conducted in Malaysia in 1995.*

***Results****: The proposed models 1 and 2 provided an accepted fit to the observed data, where for model 1 (* $\chi^2(20) = 26.15, p\text{-value} = 0.16$ *) and for model 2 (* $\chi^2(22) = 27.10, p\text{-value} = 0.21$*), indicating that the proposed models were acceptable in interpreting the hypothesized relationships. Bollen's incremental fit-index values were examined as these are least biased due to non-normality of studied variables and they were found most of them close to 0.95. The estimated effect of prosperity factor on mortality factor (*$\eta_2 \rightarrow \eta_1$*) was found significant for both models with (* $\hat{\beta}_{12} = -0.38, t = -3.65$*) for model 1 and (*$\hat{\beta}_{12} = -0.38, t = -3.62$*) for model 2. The estimated total effect of PR_EDC indicator was found significant for both models with (*$\hat{\gamma}_{11} + \hat{\gamma}_{21}\hat{\beta}_{12} = 0.09,\ t = 1.95$*) for model 1 and (*$\hat{\gamma}_{11} + \hat{\gamma}_{21}\hat{\beta}_{12} = 0.09,\ t = 1.98$*) for model 2.* ***Conclusions****: We didn't find in general significant relationship between educational indicators and mortality factor, but negatively significant relationship was found between prosperity factor and mortality factor.*

**Keywords:** infant, neonatal, stillbirth, mortality, education, prosperity, MIMIC models.

## *Introduction*

More than 10,000 newborn babies die every day (Austin and Wolfe, 1991). Every year, it is estimated that under nutrition contributes to the deaths of about 5.6 million children under the age of five; 146 million children in the developing world are underweight and at increased risk of an early death (UNICEF, 2006). Over the past half century the link between education and health and mortality has been one of the most widely documented findings in sociological research. The enormous body of evidence accumulated to date shows a robust positive association between educational attainment and a variety of health outcomes (Crimmins and Saito, 2001; Lynch 2003; Feldman et al. 1989). Although the causal relationship between education and mortality appears to be well established, its explanation is still not entirely clear.

There is a pervasive tendency for children born in socially disadvantaged families to have poorer health, education, and general welfare. In particular, there have been a large number of studies have examined the linkages between family socioeconomic conditions and the health (Lee et al. 2002; Lynch et al. 2002). Pampalon et al. (2008) modeled the changes in the association between premature mortality (deaths occurring at an early age) and a deprivation index in four geographic settings in Québec where mortality rates are modeled using negative binomial regressions, and their results showed that social inequalities in premature mortality increase everywhere in Québec except in the Montréal metropolitan area, and the highest mortality rates among deprived groups were found in mid-size cities, small towns and rural areas. Relative deprivation, often measured through income inequalities, is regularly associated with higher mortality rates and lower standards of population health (Ross, 2004; Wilkinson and Pickett, 2006).

For some authors, socioeconomic status operates mainly in mortality through proximate risk factors such as health related behaviours (e.g., smoking and nutrition), access to health care and psychosocial processes due to relative deprivation (Adler et al. 1994; Wilkinson and Pickett, 2006). For others, social position also gives access to a wide range of useful resources for health such as money, knowledge, prestige, power and beneficial social networks (Phelan et al. 2004).

A combination of behavioural, social, and economic risks mediates the association between education and incidence (Dupre, 2008). Levene (2005) stated that rising levels of nutrition among mothers were translated into improved fetal viability and reduced levels of very early mortality in London in the second half of the eighteenth century. Katz et al. (2003) used regression analysis to study early infant mortality in Nepal which may help inform the design of intervention strategies. They found that some demographic and socioeconomic factors were not associated with mortality such as husband's occupation, ownership of land, house construction and household size, while the level of education for the parents has an effect on decreasing the rate of infant mortality. Heritage (2009) stated that France has large social class health inequalities especially relating to male premature mortality; he found that less than good self-rated health was significantly more likely to be reported by people in low education, social-professional and income groups.

People with high monthly income had high total "health promotion lifestyle profile" scores, and their scores for self-actualization, health responsibility, exercise, nutrition, and stress management were higher than those with lower monthly incomes (Pirincci et al. 2008). All assumed models in this study were fitted using programming based on linear structural relationship (LISREL) software. The objective is to examine the relationship between three indicators of education: the percentages of population who achieved primary, secondary and tertiary education, prosperity factor which includes three indicators: the percentages of CLASS1, CLASS2 and CLASS3 of occupation and mortality factor which also includes three indicators: standardized infant, neonatal and stillbirth mortality ratios using partially latent models.

## Materials and methods

### Data

The data were collected from the Department of Statistics (1995) based on the census of 81 districts conducted in peninsular Malaysia. We must construct on the basis of the prior concept or statistical analyses, which particular *indicators* load on each latent variables. More precisely, we construct the following latent variables with their respective indicators:

**Mortality factor***:* mortality latent factor constructed from three indicators which are: standardized infant mortality ratio (SIMR), standardized neonatal mortality ratio (SNMR), and standardized stillbirth mortality ratio (SSMR). Infant mortality indicates the deaths under one year of age. Neonatal mortality refers to the deaths within 28 days after birth. Stillbirth occurs after 24 weeks of gestation (Hansell and Aylin, 2000). Standardization is a set of procedures for controlling the effects of external factors. Standardized Mortality Ratio ( $SMR$ ) allows comparison of the causes of death between population groups. It is calculated as follows (Pollard et al. 1974):

$$SMR_{ij} = \frac{O_{ij}}{\left( \sum_{j=1}^{80} O_{ij} \Big/ \sum_{j=1}^{80} L_{ij} \right) \times L_{ij}}, \qquad i = 1, 2, 3 \quad \text{and} \quad j = 1, 2, ..., 81$$

where, $SMR_{ij} =$ Standardized Mortality Ratio for $ith$ type of mortality and $jth$ district ( $i = 1$ for SIMR; $i = 2$ for SNMR; and $i = 3$ for SSMR). $O_{ij} =$ observed number of deaths for $ith$ type of mortality and $jth$ district. $L_{ij}$ , represents the number of live births *for infants* ( $i = 1$ ), $L_{ij}$ , represents the number of live births *for neonatals* ( $i = 2$ ), while $L_{ij}$ represents the number of live births *plus* the number of stillbirths *for stillbirths* ( $i = 3$ ).

**Education indicators:** education indicators were as follows: percentages of population who achieved (primary, secondary and tertiary) education. A strong public economy resulting from a high average education may allow more generosity with respect to social support, and high individual incomes may trigger the establishing of some smaller private health services. Another possibility is that a higher level of education may increase the chance that the individual has a well paid job in the advanced service sector, which may offer some health advantages. Education attainment is associated with infant mortality.

It may reflect a person's capacity to absorb new information and to act on it (Nordstrom et al. 1993). Education could influence the health of the community's infants and adults through normative behaviour concerning infant care and adult cigarette smoking as well as diet (Ross and Wu, 1995). The focus is on education levels, which are readily available, often used, and theoretically meaningful indicator.

**Prosperity factor:** Indicators of prosperity refer to the level of economic attainment of the district. These indicators described the type of occupation status for people living in the district. Three classes of occupation, starting from top to bottom in the income and social level were used as follows: CLASS1 includes professional, administrative and managerial workers; CLASS2 includes clerical workers; and CLASS3 includes sales, and service workers. All classes are measured in percentages. Income provides necessities such as food and health care; and low income status was found as one of the important factors for the people to have poorer health than those with higher income status (Rural Health Series, 2005; Hosseinpoor et al. 2005). It is important to relate health to prosperity (Townsend et al. 1988).

**Analysis**

Bollen (1989) argued that the structural equation modeling (SEM) or hierarchical approach had two advantages. First, this approach permits the integration of a range of measures or indicators of socioeconomic status (SES), thus avoiding the problems with choosing a single indicator. Secondly, this method allows greater control for measurement error.

**MIMIC or partially latent models***:* the term MIMIC stands for Multiple Indicators and Multiple Causes (Jöreskog and Sörbom, 2001). The MIMIC model involves two types of models: the measurement model (outer model), which relates the indicators to the latent variables and the structural model (inner model), which explain the relationship between latents. The structural equation model is: $\boldsymbol{\eta} = \boldsymbol{\Gamma}\mathbf{x} + \boldsymbol{\zeta}$, and measurement model for $\mathbf{y}$: $\mathbf{y} = \boldsymbol{\Lambda}\boldsymbol{\eta} + \boldsymbol{\varepsilon}$, where $\mathbf{y}$ is a $p \times 1$ vector of response variables, $\mathbf{x}$ is a $q \times 1$ vector of predictors, $\boldsymbol{\eta}$ is an $m \times 1$ random vector of latent dependent, or endogenous variables, $\boldsymbol{\varepsilon}$ is a $p \times 1$ vector of measurement errors in $\mathbf{y}$, $\boldsymbol{\Lambda}$ is a $p \times m$ matrix of coefficients of the regression of $\mathbf{y}$ on $\boldsymbol{\eta}$. The coefficients of $\boldsymbol{\Lambda}$ are the weights or factor loadings that relate the observed measures to the latents. The $\boldsymbol{\Gamma}$ is an $m \times q$ matrix of coefficients of the $x$-variables in the structural relationship. The elements of $\boldsymbol{\Gamma}$ represent direct causal effects of $x$-variables on $\eta$-variables. The $\boldsymbol{\zeta}$ is an $m \times 1$ vector of random disturbances in the structural relationship between $\boldsymbol{\eta}$ and $\mathbf{x}$, where in this study: $p = 3, q = 3$ and $m = 1$. The random components in LISREL model are assumed to satisfy the following minimal assumptions: $\boldsymbol{\varepsilon}$ is uncorrelated with $\boldsymbol{\eta}$, $\boldsymbol{\zeta}$ is uncorrelated with $\mathbf{x}$, and $\boldsymbol{\zeta}$ and $\boldsymbol{\varepsilon}$ are mutually uncorrelated. The model is identified if there are two or more latents and each latent has at least two indicators (Bollen, 1989; Kline, 1998). The models under this study are identified since each of mortality and prosperity latent variables include three indicators.

**Parameter estimation:** parameter estimation is performed by maximum likelihood (ML) estimator. The unknown parameters of the model are estimated so as to make the variances and covariances that are reproduced from the model in some sense close to the observed data. Obviously, a good model would allow very close approximation to the data.

**Fit indexes:** perhaps the most basic fit index is the likelihood ratio, which is sometimes called Chi-square ($\chi^2$) in the SEM literature. The value of the $\chi^2$-statistic reflects the sample size and the value of the ML fitting function. The fitting function is the statistical criterion that ML attempts to minimize and is analogous to the least squares criterion of regression. For a particular model to be adequate, values of indexes that indicate absolute or relative proportions of the observed covariances explained by the model such as the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), and Normed Fit Index (NFI) should be greater than 0.90 (Bollen, 1989; Hair *et al*. 1998). Comparative fit index (CFI) indicates the proportion in the improvement of the overall fit of the researcher's model relative to a null model like NFI but may be less affected by sample size. CFI should be greater than 0.90 (Kline, 1998) or Hu and Bentler (1999) endorsed stricter standards, pushing CFI to about 0.95. Another widely used index is the standardized Root Mean Squared Residual (SRMR), which is a standardized summary of the average covariance residuals. Covariance residuals are the differences between the observed and model-implied covariances. A favorable value of the SRMR is less than 0.10 (Hu and Bentler, 1999).

Another measure based on statistical information theory is the Akaike Information Criterion (AIC). It is a comparative measure between models with different numbers of latents. AIC values closer to zero indicate better fit and greater parsimony (Bollen, 1989; Hair *et al*. 1998). The parsimonious goodness-of-fit index (PGFI) modifies the GFI differently from the AGFI; where the AGFI's adjustment of the GFI is based on the degrees of freedom in the estimated and null models. The PGFI is based on the parsimony of the estimated model (Hair *et al*. 1998), where this index varies between 0 and 1, with higher values indicating greater model parsimony. The Non-Normed Fit Index (NNFI) includes a correction for model complexity, much like the AGFI; a recommended value is 0.90 or greater (Hair *et al*. 1998). The Root Mean Square Error of Approximation (RMSEA) value below or equal to 0.08 is deemed acceptable (Hair *et al*. 1998) or Hu and Bentler (1999) pushes RMSEA values to smaller than 0.06 and they considered it greater than 0.10 as poor fit. RMSEA is a measure to assess how well a given model approximates the true model (Bollen, 1989).

**Path diagrams:** a popular way to conceptualize a model is using a path diagram, which is a schematic drawing of the system (model) to be estimated. There are a few simple rules that assist in creating these diagrams: ovals represent latent variables. Indicators are represented by rectangles. Directional relations are indicated using a single-headed arrow. The expression "a picture is worth a thousand words" is a very apt one for SEM. Researchers who use SEM techniques often use path-diagrams to illustrate their hypotheses and summarize the results of the analysis. Figure 1 showed a conceptualized path diagram for the proposed models, explaining the parameters required to be estimated.

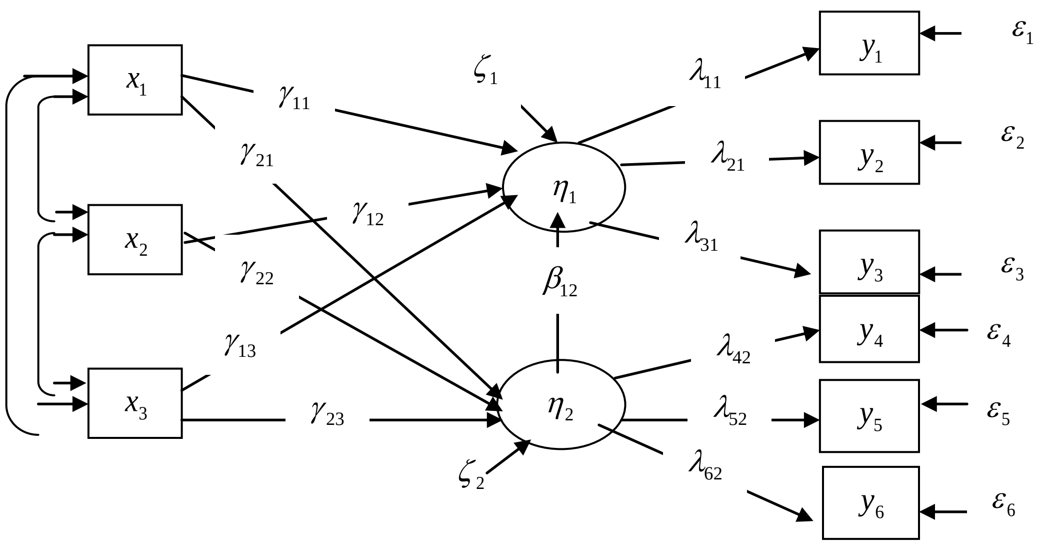


**Figure 1: Conceptualized path-diagram for the proposed models representing all variables**

## Results

Every application of SEM should provide at least the following information: a clear and complete specification of models and variables, including a clear listing of the indicators of each latent; a clear statement of the type of data analyzed, with presentation of the sample correlation or covariance matrix; specification of the software and method of estimation; and complete results (Raykov et al. 1991). However, Table 1 showed Pearson correlation matrix, mean, and standard deviation for each indicator. As shown in Table 2, we provided several indexes of goodness of fit, allowing for a detailed evaluation of the adequacy of the fitted models. The simplest gauge of how well the model fits the data would be to inspect the residual matrix as written by Field (2000). The acceptable range of residual values is one in 20 standardized residuals exceeding $\pm 2.58$ strictly by chance (Hair et al. 1998). Standardized residuals resulted from both fitting models found not exceed the threshold value, and most of them found close to zero, indicating high correspondence between elements of the implied covariances matrix of vector $\mathbf{z} = (\mathbf{y}, \mathbf{x})$, denoted as $\mathbf{\Sigma}$ and the sample covariance matrix $\mathbf{S}$. For assessing the fitted model, a model is considered adequate if the $p$-value is greater than 0.05, as 0.05 significance level is recommended as the minimum acceptance level for the proposed model (Hair et al. 1998). As shown in Table 2, we found that $p$-value for the fitted models is greater than 0.05, indicating that the proposed models are acceptable or adequate in interpreting the hypothesized relationship.

Bollen's incremental fit-index values were examined as these are least biased due to non-normality of variables and they were found most of them are close to 0.95. Figures 2 and 3 explained the estimated parameters of fitted models 1 and 2 respectively. The proposed models 1 and 2 provided an accepted fit to the observed data, where for model 1 ($\chi^2(20) = 26.15, p\text{-value} = 0.16$) and for model 2 ($\chi^2(22) = 27.10, p\text{-value} = 0.21$). The estimated (direct, indirect and total) effects of education indicators on mortality and prosperity factors with their $t$-values are shown in Table 3. The estimated effect of prosperity factor on mortality factor ($\eta_2 \to \eta_1$) is found significant for both models with ($\hat{\beta}_{12} = -0.38, t = -3.65$) for model 1 and ($\hat{\beta}_{12} = -0.38, t = -3.62$) for model 2. The estimated total effect of PR_EDC indicator was found significant for both models with ($\hat{\gamma}_{11} + \hat{\gamma}_{21}\hat{\beta}_{12} = 0.09,\ t = 1.95$) for model 1 and ($\hat{\gamma}_{11} + \hat{\gamma}_{21}\hat{\beta}_{12} = 0.09,\ t = 1.98$) for model 2.

Models 1 and 2 considered nested models (Bollen, 1989; Kline, 1998). The $\chi^2$ difference ($\chi^2_{difference}$) between two nested models should be used as criterion to know which model is better than other, where ($\chi^2_{difference} = 27.10 - 26.15 = 0.95$), which considered not significant, with degrees freedom ($22 - 20 = 2$). A non-significant value of the $\chi^2_{difference}$ statistics suggested that the overall fits of the two models were comparable.

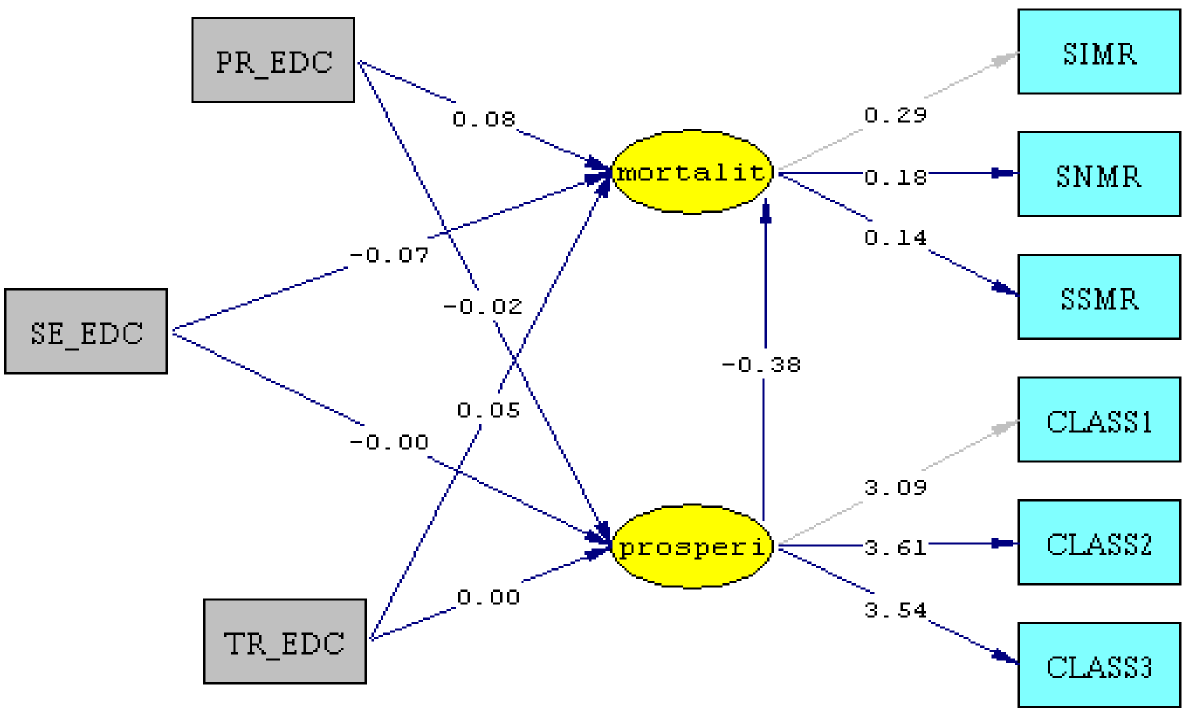


**Figure 2: Path diagram shows the results of the fitted model 1**

Models can be trimmed according to one of two standards, theoretical or empirical. Empirically, Figure 2 showed the factor loading of SNMR ($\lambda_{21} = 0.18$) closed to the factor loading of SSMR ($\lambda_{31} = 0.14$) and also factor loading of CLASS2 ($\lambda_{52} = 3.61$) closed to the factor loading of CLASS3 ($\lambda_{62} = 3.54$). Thus, the proposed model 2 represented the same relationship as shown in model 1 but with the following constraints: the factor loadings of SNMR and SSMR were equaled ($\lambda_{21} = \lambda_{31}$) and the factor loadings of CLASS2 and CLASS3 were equaled ($\lambda_{52} = \lambda_{62}$). The resulted model 2, which was explained in Figure 3, was considered better than model 1 because it was more parsimonious.

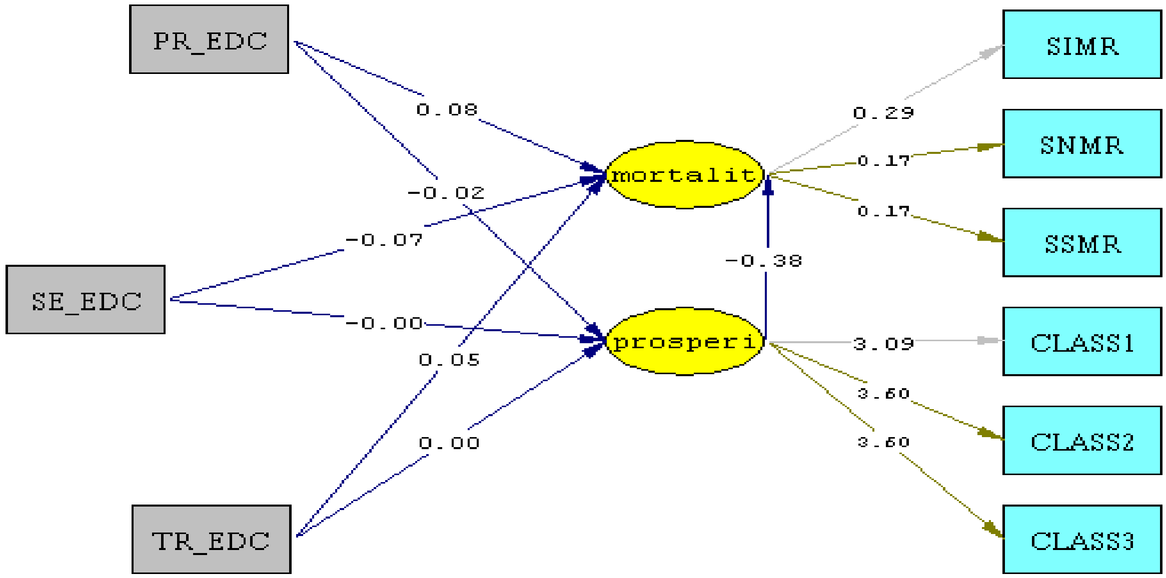


**Figure 3: Path diagram shows the results of the fitted model 2**

**Table 1: Pearson correlation matrix, Mean, and Standard Deviation (SD) for each variable**

| **Variables** | $y_1$ | $y_2$ | $y_3$ | $y_4$ | $y_5$ | $y_6$ | $x_1$ | $x_2$ | $x_3$ | **Mean** | **SD** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| SIMR, $y_1$ | 1.00 | | | | | | | | | 1.07 | 0.28 |
| SNMR, $y_2$ | $0.67^{**}$ | 1.00 | | | | | | | | 1.03 | 0.27 |
| SSMR, $y_3$ | $0.35^{**}$ | $0.25^{*}$ | 1.00 | | | | | | | 1.07 | 0.40 |
| CLASS1, $y_4$ | $-0.40^{**}$ | -0.16 | -0.12 | 1.00 | | | | | | 10.07 | 3.30 |
| CLASS2, $y_5$ | $-0.35^{**}$ | -0.13 | -0.25 | $0.88^{**}$ | 1.00 | | | | | 6.82 | 3.84 |
| CLASS3, $y_6$ | $-0.28^{*}$ | -0.12 | -0.11 | $0.66^{**}$ | $0.68^{**}$ | 1.00 | | | | 18.36 | 4.98 |
| PR_EDC, $x_1$ | 0.14 | 0.22 | 0.03 | -0.15 | -0.16 | -0.08 | 1.00 | | | 68.54 | 6.50 |
| SE_EDC, $x_2$ | 0.06 | 0.14 | -0.06 | -0.14 | -0.14 | -0.14 | $0.91^{**}$ | 1.00 | | 45.80 | 8.94 |
| TR_EDC, $x_3$ | 0.04 | 0.08 | -0.12 | -0.12 | -0.10 | -0.11 | $0.71^{**}$ | $0.86^{**}$ | 1.00 | 6.17 | 3.28 |

$^{**}$Correlation is significant at the 0.01 level (2-tailed)
$^{*}$Correlation is significant at the 0.05 level (2-tailed)

**Table 2**: Comparison between the proposed models using fit indexes

| **Fit-indexes** | **Model 1** | **Model 2** |
|---|---|---|
| *Absolute-Fit measures* | | |
| $\chi^2$-statistic( $p$-value )<br>$d.f$ | 26.15(0.16)<br>20 | 27.10(0.21)<br>22 |
| GFI | 0.93 | 0.93 |
| SRMR | 0.05 | 0.05 |
| RMSEA | 0.059 | 0.053 |
| *Incremental-Fit measures* | | |
| CFI | 0.98 | 0.99 |
| AGFI | 0.85 | 0.86 |
| NFI | 0.94 | 0.93 |
| NNFI | 0.97 | 0.98 |
| *Parsimonious-Fit measures* | | |
| PGFI | 0.41 | 0.45 |
| AIC | 75.57 | 72.86 |

$\chi^2$-statistic = Likelihood-Ratio Chi-Square Statistic, GFI = Goodness-of-Fit Index, SRMR = Standardized Root Mean Square Residual, RMSEA = Root Mean Square Error of Approximation, CFI = Comparative fit index, AGFI = Adjusted Goodness-of-Fit Index, NFI = Normed Fit Index, NNFI = Non-Normed Fit Index (An old name for the NNFI is the Tucker-Lewis Index TLI), PGFI = Parsimonious Goodness-of-Fit Index, AIC = Akaike Information Criterion.

**Table 3: Standardized estimated parameters of the effects of the indicators on latent variables with their $t$-values in parentheses**

| Type of effect | Model 1 | Model 2 |
|---|---|---|
| Direct effect: | | |
| $\hat{\gamma}_{11}$ | 0.08(1.89) | 0.08(1.92) |
| $\hat{\gamma}_{12}$ | -0.07(-1.63) | -0.07(-1.64) |
| $\hat{\gamma}_{13}$ | 0.05(0.76) | 0.05(0.74) |
| $\hat{\gamma}_{21}$ | -0.02(-0.50) | -0.02(-0.50) |
| $\hat{\gamma}_{22}$ | 0.00(-0.06) | 0.00(-0.06) |
| $\hat{\gamma}_{23}$ | 0.00(0.04) | 0.00(0.04) |
| $\hat{\beta}_{12}$ | -0.38(-3.65) | -0.38(-3.62) |
| Indirect effect: | | |
| $\hat{\gamma}_{21}\hat{\beta}_{12}$ | 0.01(0.49) | 0.01(0.49) |
| $\hat{\gamma}_{22}\hat{\beta}_{12}$ | 0.00(0.06) | 0.00(0.06) |
| $\hat{\gamma}_{23}\hat{\beta}_{12}$ | 0.00(-0.04) | 0.00(-0.04) |
| Total effect: Direct + Indirect | | |
| $\hat{\gamma}_{11}+\hat{\gamma}_{21}\hat{\beta}_{12}$ | 0.09(1.95) | 0.09(1.98) |
| $\hat{\gamma}_{12}+\hat{\gamma}_{22}\hat{\beta}_{12}$ | -0.07(-1.49) | -0.07(-1.49) |
| $\hat{\gamma}_{13}+\hat{\gamma}_{23}\hat{\beta}_{12}$ | 0.05(0.68) | 0.05(0.67) |

## *Discussion*

The proposed models were designed specifically to answer such questions as: Is the link between mortality and education myth or reality? From the previous studies, this link was real in some countries but what about Malaysia? Also, how much the relationship between mortality and prosperity is significant in Malaysia? In this study we found a negative significant effect for prosperity factor on mortality factor. However, the role of statistical testing is to answer these questions and to find the best model which can explain accurately the proposed relationship. The children of fathers in semi-routine occupations had infant mortality rates over 2.5 times higher than those of children whose fathers were in higher professional occupations (National statistics, 2003). Low levels of occupational security often accompany poverty status and poverty can induce serious health risks including mortality (Aber et al. 1997). Townsend et al. (1988) studied the inequalities in health among communities in different districts of the North of England and they stated that occupational class was a major factor for explaining inequalities in health and mortality.

As the level of education increases, the extent of health-related awareness, such as sanitation, nutrition and understanding risky behaviours such as smoking and preventive care, will be greater and lead to better health outcomes (Murthy, 2007). People with more education understand the importance of the timely medical attention, and able to acquire more health-related information. Furthermore, they properly evaluate the opportunity cost of their time and therefore would practice effective preventive care. Dupre (2008) examined the relationship between education, health risks, and disease onset and survival duration using Poisson regression models in US. His results suggested that education was negatively associated with low levels of income and unemployment.

It means that when the education level increases, the people who got job with high income or employed will increase, which in turn enhance the level or the degree of nutrition and the quality of medical treatment for the people and their children. When pregnant women were not adequately nourished, their children were borne at low weights, putting their survival at risk (UNICEF, 2006). Marchant et al. (2004) investigated the infant mortality who was born to women for whom detailed morbidity and socioeconomic data were collected during pregnancy, including hemoglobin. They found that the mortality rate of infants born to women with severe anaemia in pregnancy was three times compared to infants born to women who didn't have severe anaemia in rural Tanzania.

In essence, it was not necessarily that the results from this research were like or close to those found in other countries, either in magnitude, in direction or both. This may be an indication that there were country specific characteristics related to several indicators such as other occupation classes that could also be associated with health outcomes. A possible reason was that different countries differ in several matters such as the traditional behaviours for the people, the policy strategies, the social environments, the socioeconomic status, etc. With respect to model fit, researchers do not seem adequately sensitive to the fundamental reality that there is no true model, and all models are wrong to some degree, even in the population, and that the best one can hope for is to identify a parsimonious, substantively meaningful model that fits observed data adequately well (MacCallum and Austin, 2000). Given this perspective, it was clear that a finding of good fit didn't imply that a model was correct or true, but only plausible.

Finally with regards to methodology, it was important to note that we didn't claim to have established the fundamental true cause of how education and prosperity affects children mortality despite the causal analysis tag. Rather, we had taken the most widely believed theories on how education and prosperity relates to mortality.

## *Conclusions*

For both models, all estimated direct and indirect effects of education indicators on mortality and prosperity factors were found not significant. Also, for both models, the estimated effect of prosperity factor on mortality factor is found negatively significant, indicating that increasing in the level of prosperity leads to decreasing in the level of mortality. The estimated total effects of each of SE_EDC and TR_EDC indicators on mortality factor in both models were found not significant, whereas the estimated total effect of PR_EDC indicator was found positively significant, means that the higher level of primary education leads to higher level of mortality. This finding is consistent with the Norwegian study by Kravdal (2008), where he concluded that the average education in the municipality was not generally associated with mortality, but beneficial effect appears among men with college education. Collectively, these findings had important implications for public and policy debates regarding the linkages between education, prosperity and mortality. Further research is required regarding the relationship between several socioeconomic indicators and mortality in other developing and developed countries.

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