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Comparing Bayesian and Maximum Likelihood Predictors in Structural Equation Modeling of Children's Lifestyle Index

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Abstract: Several factors may influence children's lifestyle. The main purpose of this study is to introduce a children's lifestyle index framework and model it based on structural equation modeling (SEM) with Maximum likelihood (ML) and Bayesian predictors. This framework includes parental socioeconomic status, household food security, parental lifestyle, and children's lifestyle. The sample for this study involves 452 volunteer Chinese families with children 7–12 years old. The experimental results are compared in terms of root mean square error, coefficient of determination, mean absolute error, and mean absolute percentage error metrics. An analysis of the proposed causal model suggests there are multiple significant interconnections among the variables of interest. According to both Bayesian and ML techniques, the proposed framework illustrates that parental socioeconomic status and parental lifestyle strongly impact children's lifestyle. The impact of household food security on children's lifestyle is rejected. However, there is a strong relationship between household food security and both parental socioeconomic status and parental lifestyle. Moreover, the outputs illustrate that the Bayesian prediction model has a good fit with the data, unlike the ML approach. The reasons for this discrepancy between ML and Bayesian prediction are debated and potential advantages and caveats with the application of the Bayesian approach in future studies are discussed.

Keywords: Bayesian structural equation modeling; public health; maximum likelihood structural equation modeling; Gibbs sampler algorithm

1. Introduction

Children's lifestyle behaviors, such as technology usage time, home studying, physical activity, and sleep duration tend to change in non-favorable directions. Some studies indicate that the family environment is an important determinant of children's lifestyle [1]. Therefore, information on children's lifestyle is often gathered based on household environment surveys. Decision-makers can use such data to allocate resources prudently when planning activities aimed at improving the overall lifestyle of children in a particular community. For ease of interpretation, this type of information is summarized in a single value called the children's lifestyle index. It is also important to identify factors potentially affecting this index. Various studies have indicated that many factors are related to the lifestyle index of children, including parental socioeconomic status [2–4] and parental lifestyle [5]. However, there are insufficient studies on the impact of household food security on children's lifestyle. Moreover, there are links between parental socioeconomic situation and household food security [6]. Nevertheless, research on the simultaneous integration of the interrelationships among the four well-known concepts into one model remains scarce. These influential factors are interrelated and latent because they cannot be measured directly, and it is thus quite complicated to determine the lifestyle index.

Figure 1 shows the hypothesized model involving measurement and structural components used to illustrate the children's lifestyle index. Six important relationships are examined in the current research framework. The influence of socioeconomic status as an independent variable of behavior further complicates our understanding of children's lifestyle and related behaviors.

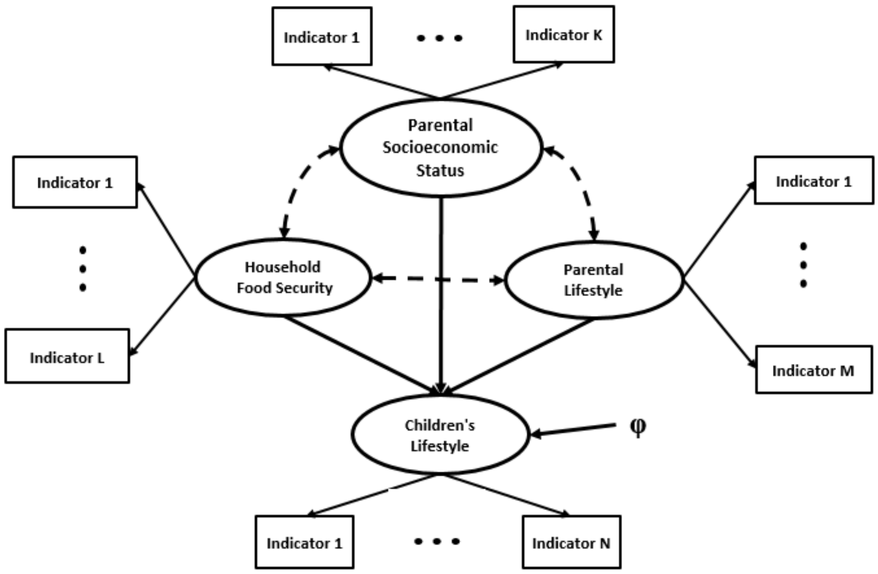

Figure 1. Research framework.

First, the direct relationships between parental socioeconomic status and children's lifestyle, as well between parental socioeconomic status and both parental lifestyle and household food security, are considered. Second, as Ishida [7] confirmed, there is an interconnection between household food security and lifestyle behavior. Therefore, these two latent variables with their relationships are included in the research model as mediators. The third relationship considers the direct impact of both household food security and parental lifestyle on children's lifestyle. The goal is to distinguish how these two family environment indicators influence children's lifestyle.

Since it is also reasonable to hypothesize that parental socioeconomic status, household food security, and parental lifestyle are correlated, the interrelationships among these three latent variables are indicated in Figure 1 by dashed lines with double-headed arrows connecting the latent variables.

The six hypotheses considered in the research model are:

H_1: Parental socioeconomic status has a significant impact on children's lifestyle.
H_2: Household food security has a significant impact on children's lifestyle.
H_3: Parental lifestyle has a significant impact on children's lifestyle.
H_4: There is a significant relationship between parental socioeconomic status and parental lifestyle in the research model.
H_5: There is a significant relationship between parental socioeconomic status and household food security in the research model.
H_6: There is a significant relationship between household food security and parental lifestyle in the research model.

Linear and nonlinear regression analyses have become bases of modeling techniques in statistics. However, individual regression analysis for each dependent variable is hardly challenged as a realistic approach in situations where the outcomes are naturally related. Additionally, it is difficult to analyze some research frameworks using regression models when an outcome is determined not only by the direct impacts of the predictor variables but also by their unobserved common causes. Structural equation modeling (SEM) is a suitable technique that can address the above limitations by providing a robust means of studying interdependencies among a set of correlated variables. Maximum likelihood SEM (ML-SEM) has been used by many researchers to analyze a complex phenomenon involving hypothesized relationships between independent and dependent latent variables. Classical methods based on the covariance structure approach encounter serious difficulties when dealing with complicated models and/or data structures. ML-SEM is applied to analyze the proper amount of hidden indicators (constructs or latent variable) to determine the observed indicators. ML-SEM is capable of performing concurrent analysis to illustrate the connections among observed indicators and corresponding latent variables as well as the connection among latent variables (Ullman [8]).

A computational algorithm in ML-SEM is developed based on the sample covariance matrix. ML-SEM employs the assumption that the observations are independent and identically distributed according to multivariate normal distribution [9]. If this assumption is not fulfilled, the sample covariance matrix cannot be determined in the usual way and is difficult to obtain [10]. Therefore, a number of researchers, such as Bashir and Schilizzi [11], Radzi and Jenatabadi [12], and Scheines and Hoijtink [13] have proposed using the Bayesian approach in SEM to overcome these problems. The Bayesian approach is attractive as users are able to employ prior information to update current information pertaining to the parameters of interest.

In his book *Structural Equation Modeling: A Bayesian Approach*, Lee [9] presents some advantages of Bayesian SEM (B-SEM) prediction:

- First moment properties of raw individual observations are mainly used in statistical techniques, thus making the techniques much simpler than second moment properties of the sample covariance matrix. Hence, B-SEM is easier to apply in more complex states.
- Direct latent variable estimation is possible, which simplifies the process of obtaining factor score estimates compared to classical regression methods.
- As manifest variables are directly modeled with their latent variables using familiar regression functions, B-SEM provides a more direct interpretation. It can also use common methods of regression modeling, such as residual and outlier analyses in conducting statistical analysis.

As pointed out by Scheines and Hoijtink [13], Lee and Song [14], and Dunson [15], the Bayesian predictor technique allows researchers to use prior experts' theories in addition to the sample information to produce better outputs and deliver valuable statistics and indices, including the mean and percentiles of the posterior distribution of unknown parameters. In conclusion, more reliable results can be achieved for small samples. In contrast, the Bayesian approach has much more flexibility in handling complex situations. Even though many studies have been done on determining the lifestyle index, not much has been done on modeling this index using SEM, particularly when considering information on parental socioeconomic status, household food security, and parental lifestyle. Therefore, the main purpose of this study is to illustrate the worth of ML-SEM and Bayesian SEM (B-SEM) in developing a model that describes the lifestyle index of children.

2. Theoretical Background of Maximum Likelihood-Structural Equation Modeling (ML-SEM) and Bayesian-SEM (B-SEM)

In the field of SEM, new techniques and statistical prediction analyses have been developed to better evaluate more complex data structures. These contain but are not limited to: linear/nonlinear SEM with covariates [16,17], SEM with multilevel dimensions [18,19], SEM with multi-samples [20,21], SEM analysis with categorical data [22,23], SEM with exponential indicators [24], and SEM with nonlinear correlations [25,26]. The above research works endeavor not only to prepare theoretical results but also to produce significant practical values. Indeed, the B-SEM technique is developed based on a Bayesian approach as the second generation of ML-SEM, which involves a much wider class of models [9].

2.1. ML-SEM

SEM is strongly capable of hypothesizing any types of relations and interactions among research variables in a single causal framework. This technique is helpful for researchers to better understand the concept of latent variables and their action within the model. Based on Bollen 's [27] study, "latent variables provide a degree of abstraction that permits us to describe relations among a class of events or variables that share something in common". For instance, with this ability of latent variables of SEM, we were able to combine indicators that are related to children's behavior in a household environment and named it the "children's lifestyle" latent variable. Another capability of SEM is determining the interconnection between three predictors (parental socioeconomic status, household food security, and parental lifestyle) and the impact of them on children's lifestyle (see Figure 2).

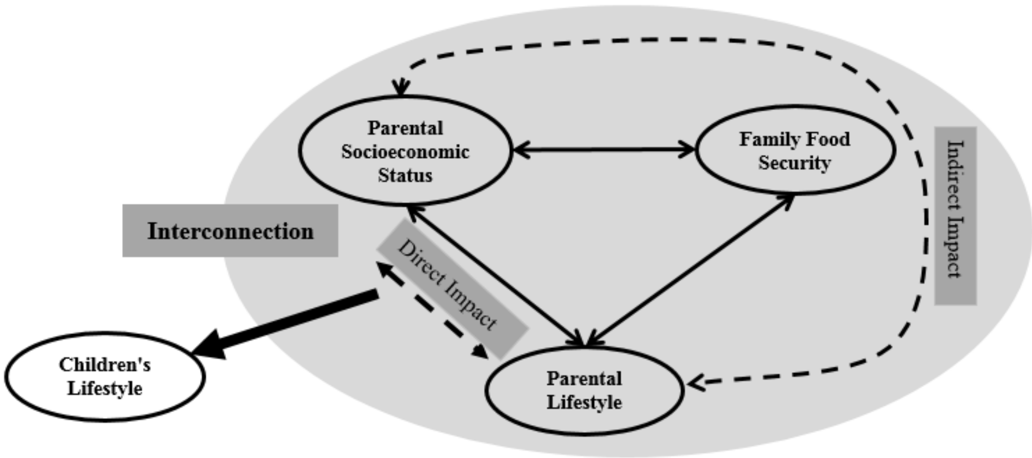

Figure 2. Interconnection among family environment variables and impact on children's lifestyle.

For predicting and estimating the research parameters in ML-SEM, measurements and structural models are the main procedures. The measurement model is defined by a $p \times 1$ vector y_i that is given by:

$$y_i = \mu\Omega_i + \varepsilon_i;\ i = 1, 2, \ldots, n \quad (1)$$

where

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix};\ \Omega = \begin{bmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_n \end{bmatrix};\ \mu = \begin{bmatrix} \mu_{11} & \mu_{12} & \cdots & \mu_{1n} \\ \mu_{21} & \mu_{22} & \cdots & \mu_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{m1} & \mu_{m2} & \cdots & \mu_{mn} \end{bmatrix};\ \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}.$$

In the research model Y includes five indicators: technology use, hours of study at home, child's physical exercise, child's sleep amount, and school grade (see Section 3.1).

In Equation (1):

(a) μ is a $(m \times n)$ matrix that represents factor loadings from modeling the regressions of y_i on Ω_i.
(b) Ω_i is a $(n \times 1)$ vector with normal distribution $N(0, \Phi)$ and is representative of the constructs (latent variables). $\Omega_i\ i = 1, \ldots, n$, are identically independent, have no correlation with ε_i, and have normal distribution $N(0, \Phi)$. To modify the exogenous and endogenous latent variables' association, Ω_i is partitioned into (λ_i, ω_i), where λ_i and ω_i are $r \times 1$ and $s \times 1$ vector variables, respectively, with latent structures.
(c) ε_i is a $(m \times 1)$ random vector with $N(0, \psi_\varepsilon)$ distribution that represents the error measurement.

Equation (2) presents the structural function elements:

$$\lambda_i = \Sigma\lambda_i + \gamma\omega_i + \pi_i;\ i = 1, 2, \ldots, n, \quad (2)$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} & \cdots & \boldsymbol{\Sigma}_{1r} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} & \cdots & \boldsymbol{\Sigma}_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\Sigma}_{r1} & \boldsymbol{\Sigma}_{r2} & \cdots & \boldsymbol{\Sigma}_{rr} \end{bmatrix}; \gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1s} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{r1} & \gamma_{r2} & \cdots & \gamma_{rs} \end{bmatrix},$$

where

(a) $\boldsymbol{\Sigma}$ is an $\boldsymbol{r} \times \boldsymbol{r}$ matrix of structural parameters representing the relationships among endogenous latent variables. This matrix is assumed to have zeroes in the diagonal elements.
(b) γ is an $\boldsymbol{r} \times \boldsymbol{s}$ matrix of regression parameters relating both exogenous and endogenous latent variables, and $\boldsymbol{\pi_i}$ is a $\boldsymbol{r} \times \mathbf{1}$ vector of disturbances.
(c) $\boldsymbol{\pi_i}$ is an error term presumed to have $\boldsymbol{N}(\mathbf{0}, \boldsymbol{\psi_\pi})$ distribution, where $\boldsymbol{\psi_\pi}$ is a diagonal covariance matrix and this vector is uncorrelated with $\boldsymbol{\omega_i}$.

In this paper children's lifestyle is the endogenous latent variable and parental socioeconomic status, household food security, and parental lifestyle are exogenous latent variables for dependent variable. However, parental lifestyle and household food security are endogenous latent variables for parental socioeconomic status. Therefore, in the research model parental socioeconomic status acts as exogenous, children's lifestyle acts as endogenous, and household food security and parental lifestyle act both endogenous and exogenous.

To estimate the research parameters with ML-SEM, the robust-weighted least-squares (RWLS) procedure is used. RWLS incurs standard errors, estimates the research parameter coefficients, calculates χ^2 and fit indices created by applying the diagonal weight matrix components produced based on the thresholds' asymptotic variances, and estimates the latent correlation [28]. Model evaluation is the next step in ML-SEM. In this respect, the model goodness-of-fit can be checked through the related Chi-square statistic (CMIN), normed fit index (NFI), comparative fit index (CFI), Tucker Lewis index (TLI), incremental fit index (IFI), relative fit index (RFI), goodness-of-fit index (GFI), and root mean square error of approximation (RMSEA) [8].

2.2. B-SEM

The ML method finds estimates by maximizing the likelihood function, assuming observed data. Specifically, if $x = (x_1, \ldots, x_n)$ is the observed value of a random sample $X = (X_1, \ldots, X_n)$ from distribution $f(\cdot)$, $f \in \mathcal{F} = \{f(x|\theta) : x \in \chi, \theta \in \Omega\}$, then the likelihood function of θ has the form

$$\mathcal{L}(\theta) = f(x_1, \ldots, x_n|\theta) = \prod_{i=1}^{n} f(x_i|\theta). \quad (3)$$

The ML estimate of θ is given by

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \mathcal{L}(\theta) \quad (4)$$

Before observing the data in Bayesian analysis, the practitioner/expert has an idea/belief/information about the unknown parameter $\theta \in \Omega$. This prior information is updated with information obtained from the sample, forming the posterior distribution of θ, which will be used to estimate θ. This procedure is shown in Figure 3, where the distributions for a prior and its respective posterior for a given parameter, together with the likelihood, are illustrated. Note that the likelihood can be considered the distribution of the data given the parameter values. Based on Figure 3, the major portion of the prior distribution has lower parameter values than the likelihood distribution. The posterior is obtained as a compromise between the prior and the likelihood.

From Figure 3, it is apparent that the prior does not allocate sufficient probability where the likelihood is high, and there exists prior-data conflict. See Evans and Moshonov [29] for more details.

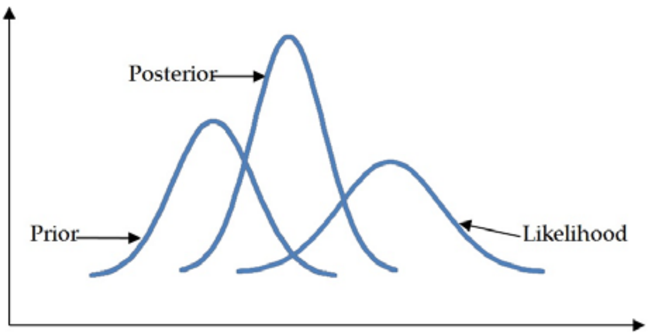

Figure 3. Likelihood, posterior, and prior for a parameter (source: [30]).

Priors can be non-informative or informative. A non-informative prior, also named a diffuse prior, can, for instance, have a normal or uniform distribution with large variance. In statistical modeling, a large uncertainty in the parameter value is reflected by a large variance. Consequently, with a large prior variance, the likelihood contributes relatively more information to the construction of the posterior, and the estimate is closer to an ML estimate. Evans [31] cautioned that using a large variance prior may lead to the Jeffreys-Lindley paradox.

Formally, the formation of a posterior draws on Bayes's theorem. Consider the probabilities of events C and D, $P_r(C)$ and $P_r(D)$. Based on probability theory, the joint event C and D can be expressed in terms of conditional and marginal probabilities:

$$P_r(C,\ D) = P_r(C|D)\ P_r(D) = P_r(D|C)\,P_r(C) \tag{5}$$

In Equation (5), if we divide every side by $P_r(C)$ then we get:

$$P_r(D|C) = \frac{P_r(C|D)\ P_r(D)}{P_r(C)} \tag{6}$$

which is known as Bayes's theorem. By applying this theorem in modeling, it lets the data x take the role of C and the parameter value takes the role of D. Thus, the posterior can be symbolically illustrated as

$$posterior = parameter\ given\ data\ = \frac{data\ |\ parameters\ \times parameters}{data} = \frac{likelihood\ \times prior}{data} \propto likelihood\ \times\ prior \tag{7}$$

In the above formula "$\propto$" means "proportional to". More specifically, we have

$$P(\theta|x) = \frac{\mathcal{L}(\theta)\,\pi(\theta)}{m(x)} \tag{8}$$

where $\pi(\theta)$ is the prior distribution (probability) of $\theta \in \Omega$ and $m(x)$ is called the prior predictive distribution of x obtained as (for a continuous case):

$$m(x) = \int_{\Omega} \mathcal{L}(\theta)\,\pi(\theta)\,d\theta \tag{9}$$

In this study, the variables gathered are in the form of ordered categories. Yanuar and Ibrahim [32] believe that, before conducting Bayesian analysis, a threshold specification must be identified in order to treat the ordered categorical data as manifestations of a hidden continuous normal distribution. A brief explanation of the threshold specification is given below.

Suppose $\boldsymbol{X}$ and $\boldsymbol{Y}$ are defined as:

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}; Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},$$

which can be considered as the ordered categorical data matrix and latent continuous variables, respectively. Moreover, the relationship between $\boldsymbol{X}$ and $\boldsymbol{Y}$ is described by applying the threshold specification. The procedure for x_1 is described as an instant. More precisely, let

$$\boldsymbol{x_1} = c \; if \; \tau_c - 1 < \boldsymbol{y_1} < \tau_c \tag{10}$$

- c is the number of categories for $\boldsymbol{x_1}$;
- $\tau_c - 1$ and τ_c represent the threshold levels associated with $\boldsymbol{y_1}$.

For example, in the current study we assumed $c = 3$, which leads to $\tau_0 = -\infty$ and $\tau_3 = \infty$. Meanwhile, the values of τ_1 and τ_2 are calculated based on the proportion of cases in each category of x_1 using

$$\tau_k = \boldsymbol{\Phi^{-1}} \left(\sum_{r=1}^{2} \frac{N_r}{N} \right), \; k = 1, 2, \tag{11}$$

We assumed that $\boldsymbol{Y}$ is distributed as a multivariate normal. Therefore, in Equation (10) we have:

- $\boldsymbol{\Phi^{-1}}(\cdot)$ is the inverse standardized normal distribution;
- N is the total number of cases;
- N_r is the number of cases in the rth category.

Under the Bayesian SEM, $\boldsymbol{X} = (\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_n})$ and $\boldsymbol{Y} = (\boldsymbol{y_1}, \boldsymbol{y_2}, \ldots, \boldsymbol{y_n})$ are the ordered categorical data matrix and latent continuous variables, respectively, and $\boldsymbol{\Omega} = (\boldsymbol{\omega_1}, \boldsymbol{\omega_2}, \ldots, \boldsymbol{\omega_n})$ is the matrix of latent variables. The observed data $\boldsymbol{X}$ are augmented with the latent data $(\boldsymbol{Y}, \boldsymbol{\Omega})$ in the posterior analysis. The parameter space is denoted by $\boldsymbol{\Theta} = (\boldsymbol{\tau}, \boldsymbol{\theta}, \boldsymbol{\Omega})$, where $\boldsymbol{\theta} = (\boldsymbol{\Phi}, \boldsymbol{\Lambda}, \boldsymbol{\Lambda_\omega}, \boldsymbol{\Psi_\delta}, \boldsymbol{\Psi_\varepsilon})$ is the structural parameter. In line with Lee (2007), the prior model is given by

$$\pi(\boldsymbol{\Theta}) = \pi(\boldsymbol{\tau})\, \pi(\boldsymbol{\theta})\, \pi(\boldsymbol{\Omega}|\boldsymbol{\tau}, \boldsymbol{\theta}) \tag{12}$$

where, due to the ordinal nature of thresholds, a diffuse prior can be adopted. Specifically, for some constant c,

$$\pi(\boldsymbol{\tau}) = c \tag{13}$$

Further, to accommodate a subjective viewpoint, a natural conjugate prior can be adopted for θ with the conditional representation $\pi(\boldsymbol{\theta}) = \pi(\boldsymbol{\Lambda} | \boldsymbol{\Psi_\varepsilon})\, \pi(\boldsymbol{\Psi_\varepsilon})$. More specifically, let

$$\psi_{\varepsilon k}^{-1} \sim \Gamma(\alpha_{0\varepsilon k}, \beta_{0\varepsilon k}) \tag{14}$$

$$\left(\Lambda_k \middle| \psi_{\varepsilon k}^{-1} \right) \sim N(\Lambda_{0k}, \psi_{\varepsilon k} \boldsymbol{H_{0yk}}) \tag{15}$$

where $\psi_{\varepsilon k}$ is the kth diagonal element of ψ_ε, Λ_k is the kth row of $\boldsymbol{\Lambda}$, and Γ denotes the gamma distribution. Finally, an inverse-Wishart distribution is adopted for Φ as follows:

$$\boldsymbol{\Phi^{-1}} \sim W_q(R_0, \rho_0) \tag{16}$$

It is further supposed that all hyperparameters are known. Posterior distribution can be found by normalizing the product $L(\boldsymbol{\Theta} | \boldsymbol{X} = x)\, \pi(\boldsymbol{\Theta})$.

In order to sample from the posterior distribution $\Theta|X = x$, the Markov Chain Monte Carlo (MCMC) technique is used to handle the computational complexity.

2.3. Modeling Description

The model hypothesized in this study consists of 16 indicator variables with one exogenous latent variable and three endogenous latent variables. The following measurement model is then formulated:

$$y_i = \Lambda\omega_i + \varepsilon_i,\ i = 1, 2, \ldots, n \tag{17}$$

where $\omega_i = (\eta_i, \xi_{i1}, \xi_{i2}, \xi_{i3})^T$. The structural part of the current SEM model has the form

$$\eta_i = \gamma_1\, \xi_{i1} + \gamma_2\xi_{i2} + \gamma_3\xi_{i3} + \delta_i \tag{18}$$

where $(\xi_{i1}, \xi_{i2}, \xi_{i3})^T$ is distributed as $N(0, \Phi)$ and independent of δ_i, which is distributed as $N(0, \psi_\delta)$.

In data analysis, we applied AMOS 18 to estimate research parameters for ML-SEM, while WinBUGS 1.4 was used for B-SEM analysis. The hierarchical structure is employed by choosing the prior information for parameters involved in the hypothesized model, as defined in Equations (14)–(16).

3. Materials and Methods

3.1. Data Structure

The information gathered in this survey includes information about parental socioeconomic status, household food security, parental lifestyle, and children's lifestyle of individuals living in Urumqi, Xinjiang, China. The parental socioeconomic situation was measured as the initial independent variable, including nine indicators. Eight of the indicators are the mother's age, father's age, mother's education level, father's education level, mother's income level, father's income level, mother's work experience, and father's work experience. The added question is "How long have the parents been married? The parents' ages were classified into four groups, namely "30 years old or below", "31 to 40 years old", "41 to 50 years old" and "over 50 years old", which were coded as 1, 2, 3, and 4, respectively. With respect to education level, the responses obtained were coded as 1 for "Less than High School", 2 for "High school", 3 for "Diploma", 4 for "Bachelor's", and 5 for "Master's or PhD". The respondents were asked about the parental income status, and the responses were denoted by 1, 2, 3, 4, and 5 for "less than RMB2,000 per month", "RMB2,001–RMB3,000 per month", "RMB3,001–RMB4,000 per month", "RMB4,001–RMB5,000 per month", and "more than RMB5,000 per month", respectively. The respondents were asked about the parental work experience and the responses were coded as 1, 2, 3, 4, and 5, denoting "less than 5 years", "5–10 years", "11–15 years", "16–20 years", and "more than 20 years", respectively. The last question in the socioeconomic part is related to the duration of the parents' marriage, and responses were labeled 1, 2, 3, 4, and 5 for "less than 2 years", "2–4 years", "5–7 years", "8–10 years", and "more than 10 years". Family food security status was the first mediator, based on a study by Bickel, Nord [33], which included 18 standard questions. We extracted nine questions that are representative of the food security indicators, which were measured on a Likert scale from 1 to 9. The third variable is parental lifestyle and in the research model it acts as the second mediator. Several authors have proposed lists of health-related behaviors for measuring parental lifestyle. Nakayama and Yamaguchi [34] suggested a list of health-related behaviors including physical exercise, smoking habits, average sleeping hours, and average working hours per day. In our study, we added drinking alcohol to Nakayama's list and measured all factors for fathers and mothers separately. Therefore, parental lifestyle was measured based on 10 indicators, namely alcohol drinking, smoking habits, physical exercise, working hours, and average sleeping hours per day, for the mother and father. The respondents were asked about their alcohol drinking habits and the responses were coded as 1, 2, 3, 4, 5, 6, and 7, denoting "less than 1 time per month", "1 time per month", "2 to 3 times per month", "1 time per week", "2 to 3 times per week", "4 to

6 times per week", and "every day". The respondents were asked about their smoking habits and the responses were coded as 1, 2, and 3, denoting "smoker", "quit", and "non-smoker", respectively. Regarding the frequency of physical exercise, respondents were asked "how many times a week on average do you do physical exercise?" The responses for this question were placed into four categories coded as 1, 2, 3, and 4, indicating "none", "1 or 2 times per week", "3 or 4 times per week", and "more than 4 times per week", respectively. Working hours per day were coded as 1 for "more than 14 h", 2 for "9–14 h", and 3 for "less than 9 h". The average sleeping hours per day were grouped as 1 referring to "less than 7 h per day", 2 for "more than 8 h per day", and 3 for "between 7 and 8 h per day". Children's lifestyle was the fourth latent variable and acted as the dependent variable. Five indicators were considered in measuring the children's lifestyle index. These are hours of study at home, child's sleep amount, technology use, school grade, and child's physical exercise. The average hours of study at home per day were grouped into four categories: 1 referring to "less than 1 h per day", 2 for "1 to 2 h per day", 3 for "3 to 4 h per day", and 4 for "more than 4 h per day". The child's average sleeping hours per day were grouped into 1 referring to "less than 7 h per day", 2 for "between 7 and 8 h per day", 3 for "between 8 and 9 h per day", and 4 for "more than 9 h per day". Respondents were asked "how many hours on average does your child use technology per day?" The responses for this question consist of four categories that were coded as 1, 2, 3, and 4, indicating "less than 1 h per day", "1 to 2 h per day", "3 to 4 h per day", and "more than 4 h per day", respectively. Children's school levels were coded from 1 to 6, denoting grades 1 to 6. Children's physical activity per week was coded as 1 for "none", 2 for "1 or 2 times per week", 3 for "3 or 4 times per week", and 4 for "more than 4 times per week".

3.2. Ethics Statement

For this research, the questionnaires were self-administered/reported. These surveys were collected anonymously, with no way of identifying the participants. Therefore, based on the Health Research Ethics Authority [35], the research does not require an ethics review "based solely on the researcher's personal reflections and self-observation".

3.3. Sampling

Five primary schools were selected from Urumqi City, Xinjiang Province, China and 120 questionnaires were delivered to every school. Every primary school includes six grades, and 20 questionnaires were distributed to each grade. Therefore, $5 \times 6 \times 20 = 600$ questionnaires were distributed in 2014 to five schools. Every questionnaire was for one family including a father, a mother, and a child between seven and 12 years old. The sample comprised parents who joined school parent meetings that take place four times per year. For each of the six grades, 20 volunteers were selected and trained on filling out the questionnaire. The survey was conducted with University of Malaya funding. A parent was retained in the sample if they had a child between seven (grade 1) and 12 (grade 6) years of age.

Of 600 distributed questionnaires, 483 were returned. The rest of the families refused to continue their cooperation. Among 483 questionnaires, 22 were eliminated based on missing data. Mahalanobis distance is an extremely general measure that is utilized for the measurement of multivariate outliers [36]. Based on Mahalanobis Distance testing, nine observations (observation number; 36, 88, 92, 134, 228, 256, 372, 411, and 444) were eliminated from the list because they were considered outliers that could affect the model fit, R^2, and the size and direction of parameter estimates (see Table 1). Therefore, $(483 - 22 - 9 = 452)$ 452 observations were considered as the final data of the study.

Table 1. Mahalanobis distance.

Observation Number	Mahalanobis D-Squared	*p*1	*p*2
36	22.56	0.0016	0.0084
88	20.31	0.0067	0.0091
92	18.92	0.0092	0.0104
134	36.58	0.0116	0.0124
228	32.71	0.0231	0.0178
256	30.08	0.0854	0.0364
372	28.19	0.0932	0.0392
411	25.44	0.1589	0.0421
444	19.76	0.2876	0.0482

If *p*1 or *p*2 is less than 0.05 then the observation is an outlier.

4. Results

Tables 2 and 3 show a descriptive analysis of the child and parental characteristics.

Table 2. Descriptive analysis of child characteristics.

Characteristics	Percentage	Characteristics	Percentage
Gender:		***Average hours per day of using technology:***	
Boy	45.60%	Less than one hour per day	13.20%
Girl	54.40%	1 to 2 h per day	15.70%
School grades:		3 to 4 h per day	40.70%
Grade 1	14.20%	More than 4 h per day	30.70%
Grade 2	16.80%	***Physical activities in a week:***	
Grade 3	16.60%	None	44.20%
Grade 4	16.30%	1 or 2 times per week	28.40%
Grade 5	17.30%	3 or 4 times per week	19.70%
Grade 6	18.80%	More than 4 times per week	7.70%
Study at home:		***Average sleeping hours in a day:***	
Less than one hour per day	21.10%	Less than 7 h per day	5.80%
1 to 2 h per day	29.40%	Between 7 and 8 h per day	22.20%
3 to 4 h per day	33.10%	Between 8 and 9 h per day	56.30%
More than 4 h per day	16.40%	More than 9 h per day	15.70%

Only the essential factors of each latent variable were sustained in the research model by applying factor loading. Table 4 presents the indicators' factor loadings on three latent variables. According to Argyris and Schön [37], the standardized factor loading must be over 0.5. As illustrated in Table 4, some factor loadings of four latent variables are below 0.5; therefore, these indicators must be excluded from the measurement model. For the parental socioeconomic latent variable, six indicators were excluded from the research model. These are the mother's age, father's age, father's education, mother's income, mother's work experience, and father's work experience. For the parental lifestyle latent variable, five indicators were excluded from the research model. These are the mother's alcohol drinking habit, mother's smoking habit, father's smoking habit, mother's physical exercise habit, and father's physical exercise habit. Among nine indicators of household food security, four were excluded from the research model. Finally, two indicators of children's lifestyle were excluded from the research model, the child's physical exercise habit and school grade.

Table 3. Descriptive analysis of parental characteristics

Characteristics	Father (%)	Mother (%)	Characteristics	Father (%)	Mother (%)
Age:			*Smoking Habit:*		
Less than or equal 30 years old	18.5%	21.6%	Smoker	66.6%	23.8%
Between 31and 40 years old	36.2%	25.1%	Quitted	15.7%	13.7%
Between 41 and 50 years old	22.1%	28.4%	Non-smoker	17.7%	62.5%
More than 50 years old	23.2%	24.9%	*Physical exercise:*		
Education:			None	54.4%	33.6%
Less than High School	11.3%	9.5%	1 or 2 times in a week	27.7%	38.7%
High school	19.8%	6.7%	3 or 4 times per week	14.8%	11.2%
Diploma	37.7%	41.9%	More than 4 times in a week	3.1%	16.5%
Bachelor	29.1%	33.1%	*Working hours in a day:*		
Master or PhD	2.1%	8.8%	More than 14 hours per day	26.7%	8.2%
Income:			9–14 hours per day	62.8%	73.5%
Less than RMB2000 per month	11.7%	20.6%	Less than 9 hours per day	10.5%	18.3%
RMB2001-RMB3000 per month	22.6%	24.5%	*Average sleeping hours in a day:*		
RMB3001-RMB4000 per month	33.9%	22.1%	Less than 7 hours per day	55.4%	61.9%
RMB4001-RMB5000 per month	19.9%	17.3%	Between 7 to 8 hours per day	27.9%	30.0%
More than RMB5000 per month	11.9%	15.5%	More than 8 hours per day	16.7%	8.1%
Work experience:			*Drinking Alcohol Habit:*		
No work experience	0.00%	0.00%	Less than one time per month	3.2%	10.6%
Less than 5 years	7.4%	19.2%	1 time per month	4.5%	22.7%
5-10 years	12.9%	21.7%	2 to 3 times per month	16.1%	32.1%
11-15 years	36.6%	26.6%	1 time per week	16.7%	28.2%
16-20 years	32.8%	23.6%	2 to 3 times per week	39.5%	6.4%
More than 20 years	10.3%	8.9%	4 to 6 times per week	18.7%	0.00%
			Every day	1.3%	0.00%

Table 4. Factor loading analysis of research latent variables.

Parameter Description	Factor Loading
Parental Socioeconomic	
Mother's age	0.43
Father's age	0.38
Mother's education	0.74
Father's education	0.39
Mother's income	0.43
Father's income	0.68
Mother's work experience	0.06
Father's work experience	0.05
Parents' marriage length	0.82
Parental Lifestyle	
Mother's drinking alcohol	0.36
Father's drinking alcohol	0.73
Mother's smoking habit	0.48
Father's smoking habit	0.41
Mother's physical exercises	0.21
Father's physical exercises	0.09
Mother's working hours	0.76
Father's working hours	0.88
Mother's average sleeping hours	0.83
Father's average sleeping hours	0.71

Table 4. *Cont.*

Parameter Description	Factor Loading
Household Food Security	
Worry about running out of food	0.73
Do not have money: household	0.82
Cannot afford to eat balanced meals: household	0.93
Cut down food portions: household	0.12
Do not eat the whole day: adults	0.98
Do not have money: children	0.04
Cannot afford to eat balanced meals: children	0.25
Cannot afford enough food: children	0.82
Skip a meal: children	0.24
Children's Lifestyle	
Technology use	0.92
Hours of study at home	0.73
Child's physical exercise	0.49
Child's sleep amount	0.68
School grade	0.46

Figure 4 represents the results of model fitting based on the SEM approach. In this respect, the model's goodness-of-fit can be checked with normed fit index (NFI), comparative fit index (CFI), Tucker Lewis index (TLI), incremental fit index (IFI), relative fit index (RFI), and goodness-of-fit index (GFI). The values of GFI, IFI, RFI, TLI, and NFI are within the acceptable range. Therefore, the current model is fitted for our data at the 5% significance level.

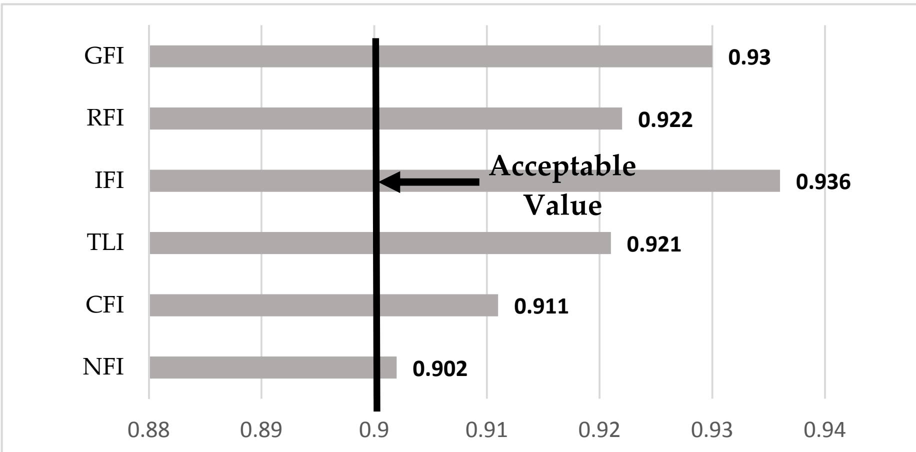

Figure 4. Model fitting analysis.

For some particular Bayesians, priors can come from any source, objective or otherwise [38]. The issue just described is referred to as the "elicitation problem" and has been discussed by Van Wesel [39] and Rietbergen and Klugkist [40]. Moreover, elicitation procedure is a time-consuming task, and even experts are often mistaken and prone to overstating their certainty [41]. Therefore, instead of depending fully on expert decisions, research scholars engaging Bayesian analysis often attempt to select the priors such that they are informative enough to yield B-SEM's advantages, while not being so informative as to bias the results [42]. By the end if one is unsure about the prior distribution, a sensitivity analysis is suggested [43]. In such an analysis, the outcomes of different prior specifications are compared to inspect the influence of the prior. To achieve this goal, models with four types of prior inputs were compared. In assigning hyperparameter values, a small variance was taken for each parameter. Fixed values of $\alpha = 5$ and $\beta = 5$ were evaluated for four inputs. Furthermore, values corresponding to $\boldsymbol{\Phi}$ were measured with $\rho_0 = 25$ and ${R_0}^{-1} = 6.5\boldsymbol{I}$.

Accordingly, the four prior inputs calculated are:

1. Prior I: Unknown loadings in $\boldsymbol{\Lambda}$ are all made equal to 0.35, and the measures corresponding to $\{\theta_1, \theta_2, \theta_3\}$ are $\{0.6,\ 0.5,\ 0.2\}$.
2. Prior II: The hyperparameter values are considered half of the values in prior I.
3. Prior III: The hyperparameter values are considered a quarter of the values in prior I.
4. Prior IV: The hyperparameter values are considered double the values in prior I.

Table 5 presents the outputs based on four types of prior inputs. This table indicates that the parameter estimates and standard errors obtained for various prior inputs are reasonably close. It can be concluded that the statistics found based on B-SEM are not sensitive to these four prior inputs. Therefore, our approach is only valid with the adopted prior and B-SEM applied here is quite robust against the different prior inputs. Accordingly, for the purpose of discussing the results obtained using B-SEM, the results obtained using type I prior are used.

Table 5. Parameter estimation and standard error for four types of prior in B-SEM analysis.

	Prior I		**Prior II**		**Prior III**		**Prior IV**	
Parameter	**Estimate**	**STD**	**Estimate**	**STD**	**Estimate**	**STD**	**Estimate**	**STD**
θ_1	0.561	0.021	0.555	0.033	0.549	0.069	0.584	0.121
θ_2	0.493	0.088	0.461	0.097	0.452	0.102	0.503	0.201
θ_3	0.203	0.096	0.192	0.051	0.180	0.091	0.221	0.138
θ_{13}	0.739	0.108	0.721	0.101	0.598	0.027	0.751	0.102
θ_{16}	0.683	0.112	0.677	0.109	0.655	0.111	0.686	0.138
θ_{19}	0.822	0.087	0.816	0.078	0.801	0.098	0.852	0.203
θ_{22}	0.733	0.039	0.730	0.035	0.722	0.069	0.763	0.093
θ_{27}	0.763	0.109	0.755	0.099	0.743	0.106	0.771	0.126
θ_{28}	0.883	0.119	0.844	0.081	0.822	0.077	0.896	0.119
θ_{29}	0.827	0.044	0.814	0.041	0.759	0.036	0.834	0.66
θ_{210}	0.711	0.066	0.697	0.057	0.666	0.051	0.723	0.107
θ_{31}	0.734	0.029	0.726	0.026	0.669	0.039	0.742	0.127
θ_{32}	0.822	0.071	0.816	0.064	0.798	0.061	0.831	0.104
θ_{33}	0.928	0.191	0.909	0.161	0.852	0.170	0.832	0.206
θ_{35}	0.981	0.058	0.921	0.052	0.832	0.048	0.883	0.067
θ_{38}	0.816	0.161	0.799	0.152	0.764	0.143	0.802	0.188

Based on Figures 5 and 6, the estimated structural equations that address the relationships between the children's lifestyle index and parental socioeconomic status, household food security, and parental lifestyle for ML-SEM and B-SEM are given by:

$$\hat{\varphi}\,(ML - SEM) = 0.549\theta_1 + 0.198\,\theta_2 + 0.488\,\theta_3 \tag{19}$$

and

$$\hat{\varphi}\,(B - SEM) = 0.561\theta_1 + 0.203\,\theta_2 + 0.493\,\theta_3 \tag{20}$$

respectively, where

θ_1 is the coefficient of parental socioeconomic status indicator;
θ_2 is the coefficient of household food security indicator;
θ_3 is the coefficient of parental lifestyle indicator.

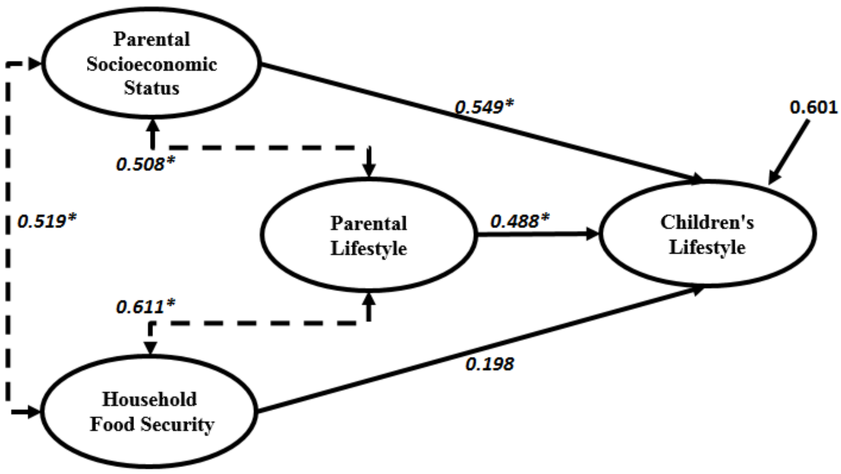

Figure 5. ML-SEM output.

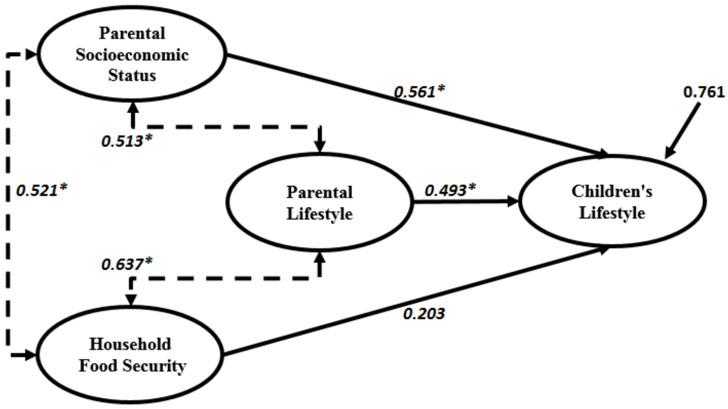

Figure 6. B-SEM output.

Table 6 presents the outputs of the research hypotheses regarding the relationships among variables in this study. In both models, the impact of parental socioeconomic status and parental lifestyle on children's lifestyle is significant. However, the impact of household food security on children's lifestyle is not significant. Moreover, the relationships between parental socioeconomic status and parental lifestyle, parental socioeconomic status and household food security, and household food security and parental lifestyle are significant and positive.

Table 6. Estimated parameters estimation of SEM using ML and Bayesian predictors.

Relation	Estimated Coefficients	
	ML-SEM	B-SEM
Parental socioeconomic → Children's life style	0.549 *	0.561 *
Household food security → Children's life style	0.198	0.203
Parental lifestyle → Children's life style	0.488 *	0.493 *
Parental socioeconomic ↔ Parental lifestyle	0.508 *	0.513 *
Parental socioeconomic ↔ Household food security	0.519 *	0.521 *
Household food security ↔ Parental lifestyle	0.611 *	0.637 *

* Presents a significant relationship with 95% confidence.

This part of the study presents an analysis of the comparison between the ML-SEM and B-SEM techniques in predicting the children's lifestyle index. Two main stages were considered in the comparison. In the first stage, four indices were used to compare ML-SEM with B-SEM, which are representative of the strength and correctness of the predictions. Among various prediction techniques, the root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MSE), and mean absolute percentage error (MAPE) are the most familiar statistical indices for comparison purposes. Table 7 presents the formulas of these indices and outputs of the ML and Bayesian approaches.

Table 7. Comparative outputs of ML-SEM and B-SEM.

Name of Index	Formula	ML-SEM Value	B-SEM Value
MAPE	$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left\| \frac{y'_i - y_i}{y_i} \right\|$	0.094	0.088
RMSE	$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{n} (y'_i - y_i)^2}{n}}$	0.091	0.051
MSE	$MSE = \frac{\sum_{i=1}^{n} \|y'_i - y_i\|}{n}$	0.128	0.105
R^2	$R^2 = \frac{[\sum_{i=1}^{n} (y'_i - \overline{y}'_i).\ (y_i - \overline{y}_i)]^2}{\sum_{i=1}^{n} (y'_i - \overline{y}'_i).\ \sum_{i=1}^{n} (y_i - \overline{y}_i)}$	0.601	0.761

In the above indices, y_i is the ith actual value of the dependent variable and y'_i is the ith predicted value. The R^2 value for the B-SEM model was greater than for the ML-SEM model, and the RMSE, MSE, and MAPE values for the B-SEM model were lower than for ML-SEM. Therefore, according to the performance indices, B-SEM predicted children's lifestyle better than the ML-SEM model. The main reason B-SEM performed better is the ML framework defined, which permits simultaneous self-adjustment of parameters and effective learning of the association between inputs and outputs in causal and complex models.

The present comparative analysis illustrates that the B-SEM has superior evaluation capability over ML-SEM in children's lifestyle index prediction. This conclusion is only made for this empirical analysis and it does not prove that B-SEM is always superior to ML-SEM.

5. Discussion

The main purpose of the present study was to demonstrate the potential of the maximum likelihood SEM and Bayesian SEM approaches in modeling the children's lifestyle index. The strength of SEM is its ability to perform a simultaneous test to describe the relationship between the observed variables and the respective unobserved variables as well as the connection among the unobserved variables. AMOS version 18 was used to analyze the data in this study, which is a flexible tool that enables researchers to examine relationships that violate the normal assumption of the variables considered in a model. Additionally, the outputs were compared by applying Bayesian SEM using winBUGS version 1.4.

In the current study, ML-SEM served as a representative parametric analysis method and B-SEM as a representative semi-parametric technique for predicting the children's lifestyle index. Based on the R^2, RMSE, MSE, and MPEA indices, SEM with the Bayesian approach was more effective at predicting children's lifestyle with the dataset obtained from Urumqi, Xinjiang, China.

Although much work has focused on determining the children's lifestyle index, not much has been done on modeling this index using SEM, particularly with Bayesian approaches. This is especially true when information on parental socioeconomic status, household food security, and parental lifestyle is concerned. The indicators that were found to be significant in explaining the latent factors considered in this study are as follows. The socioeconomic indicators are age, income, work experience, education level, and length of parents' marriage. Parental lifestyle is explained by smoking habit, frequency of engaging in physical exercise, alcohol drinking habit, number of working hours, and number of sleeping hours per day. Worry about running out of food, not having money (household), inability to afford eating balanced meals (household), cutting down food portions (household), not eating the whole day (adults), not having money (children), inability to afford to eat balanced meals (children), inability to afford enough food (children), and skipping a meal (children) served as indicators to measure household food security.

Therefore, the research model includes three predictors, which are parental socioeconomic status, parental lifestyle, and household food security. Among these, parental socioeconomic status and parental lifestyle have a significant impact on predicting children's lifestyle. However, household food security does not have a direct impact on children's lifestyle. Parental socioeconomic status was the main and first predictor in the study, as it has the highest impact on children's lifestyle. Parental socioeconomic status is a combination of nine indicators (Table 4), only three of which have acceptable factor loadings in the research model. These are the mother's education, father's income, and parents' marriage length. This means that helping a family with a longer marriage by improving the mother's education and father's income can provide better children's lifestyle quality. The second predictor was parental lifestyle, which was measured based on 10 indicators. Among these indicators, five had significant factor loadings and remained in the final research model. The five indicators are father's alcohol drinking habit, mother's working hours, father's working hours, mother's average sleeping hours, and father's average sleeping hours. This means that, in Urumqi, Xinjiang, China, controlling the father's alcohol drinking habit and optimizing both parents' working hours and average sleeping hours can lead to higher children's lifestyle quality. The third predictor was household food security, which was measured with nine indicators. Among these, five indicators had significant factor loadings (Table 4) and were considered in the final research model. Household food security does not have a direct impact on children's lifestyle. However, it has a strong significant relationship with parental socioeconomic status and parental lifestyle. Therefore, this predictor cannot be eliminated from the research model. In other words, household food security has an indirect impact on children's lifestyle with relations to parental socioeconomic status and parental lifestyle.

We proposed a Bayesian approach to analyze useful structural equations for children's lifestyle index modeling. In formulating ML-SEM and developing the Bayesian method, emphasis was placed on raw individual random observations rather than on the sample covariance matrix.

Through this study it was found that parental socioeconomic status and parental lifestyle have a significant effect on the children's lifestyle index, but household food security does not. The concept of modeling the children's lifestyle index by considering various indicators that describe latent factors can be explored further by incorporating new survey data. This idea is particularly suitable with the sequential Bayesian approach by considering the results from this study as prior input for future studies. The research framework introduced (Figure 1) can be used in any area. Hence, another suggestion for future studies is a comparison analysis modeling children's lifestyle in China and Malaysia. It is worth noting that there is a lack of evidence to indicate a connection between children's calorie intake and energy expenditure and overall lifestyle. Clinical causes and effects were not examined in the present research, so it is recommended to study them in future investigations.

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