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Determination of Physical Health Obstetrics Index Using Bayesian Confirmatory Factor Analysis (BCFA)

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ABSTRACT

An important component in the health of women, especially pregnant women is reproductive health. Reproductive health in recent decades has received special attention globally. Reproductive health is also a target of the MDGs (Millennium Development Goals) health, especially with regard to health. Reproductive health indicators one of which is physical health obstetric, so it is necessary study on the physical health index obstetric through Bayesian Confirmatory Factor Analysis (BCFA) approach). Research location is in space postpartum Obstetrics Gynecology Hospital Dr. Soewandhi Surabaya. The results showed that physical health obstetric is fit model, this is based on the percentile criteria used prior distribution is the conjugate prior distribution. The main indicators of obstetric physical health is a disease during pregnancy, doctors prescribing the drug outside, consumption of protein and smoking. Physical health obstetric index of 52 observations can be considered a high of 40.4 %, 17.3 % moderate and 42.3 % lower.

KEYWORDS: Physical health obstetric, CFA, Bayesian, Percentile, Index

1. INTRODUCTION

The main target of women's health care is to improve the quality of health both as individuals and social beings dynamic character, so it is appropriate to increase health services based on the conditions of life of individuals and society [1].An important component in the health of women, especially pregnant women is reproductive health. Reproductive health in recent decades has received special attention globally. Discussion on reproductive health has been included in the international agenda, namely the International Conference on Population and Development (International Conference of Population and Development / ICPD) in Cairo, Egypt in 1994. In this conference reached agreement on a paradigm shift in the management of population and development issues of the approach population control and fertility decline becomes more focused approach to reproductive health and reproductive rights compliance efforts.

Indicators of coverage of maternal and child health programs include the numbers of births attended by skilled health personnel, maternal mortality rate, the incidence of sepsis, the incidence of uterine rupture, the incidence of bleeding, the incidence of obstruction of labor [2].Health indicators such as the Human Development Index (HDI) linked indirectly related to reproductive health is life expectancy at birth. How to increase life expectancy, it is difficult to answer with certainty because of factors affecting life expectancy, especially related to pregnancy and reproductive health is not certain linkages. Therefore, it is necessary to study the reproductive health indicators are expected to impact directly or indirectly on maternal health, which in turn increases the life expectancy at birth.

The indicators used to measure the health of the following: a habit to go to health facilities for treatment and family planning; meat / fish / eggs as a side dish in a week; the number of children born alive; participation in community activities / politics; family members who are able to use the means of transport; the opportunity to obtain news from newspapers, radio, TV, magazines [3]. Development of women's reproductive health, particularly pregnant women is one of the determinants that affect the health of society. So the reproductive health of women, especially pregnant women are a very important aspect because very large effect on the health of the nation's child successor generation. Therefore, it should receive special attention from the government and local and global health organizations. Reproductive health indicator is a measure to describe the state of a system of reproductive health [4]. To test the validity of specific indicators, one of which is by using a Bayesian CFA [14].

Methods Confirmatory Factor Analysis with maximum likelihood approach is used to identify the indicators of reproductive health [15]. This approach requires a multivariate normal distribution of data [10]. According to Sharma (1996), [11] Confirmatory Factor Analysis (CFA) was one of the hypothesis test to prove the theory, a technique to reduce the data. CFA is one of the multivariate analysis techniques, with the focus on relationships

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together without differentiating variable dependent variable and the independent variable or a method referred to as the inter-dependence.

2. LITERATURE REVIEW

2.1 Reproductive Health

Which is used as an indicator of women's health in the areas of reproductive health is Maternal Mortality Rate (MMR). Indicators of reproductive health is a strong indicator that used the WHO along with other indicators, such as maternal mortality ratio, the child mortality rate, total fertility rate, the prevalence of HIV infection at the age of 15-24 years, the Human Development Index (HDI) [6]. Reproductive health topics were also targeted MDGs (Millennium Development Goals (MDGs)) health, especially with regard to maternal health (goal 5) as well as in the fight against HIV / AIDS and other sexually transmitted diseases (goal 6) [5].

Indicators related to reproductive health is eating habits (eating frequency, source of protein / iron), morbidity associated with reproduction, access to health care (distance and travel time), the place of delivery, birth attendants, family planning participation (types of contraceptives and family planning services) [7].

Indicators that affect the physical health of the mother in pregnancy include the mother's age, spacing pregnancies with previous deliveries, parity, height, TT immunization, infectious diseases, anemia, twin pregnancy, previous history of pregnancy and childbirth, high blood pressure [8]. Service indicators include pregnancy care coverage given midwife among others giving fe tablets to pregnant women, examination during pregnancy (K1 and K4) and scope of service delivery includes normal delivery assistance by health professionals, referral services [9].

2.2Bayesian *Confirmatory Factor Analysis* (BCFA)

CFA is a method to test how well the measured variables can represent constructs or factors preconceived [10]. CFA can be divided into two is First -Order and Second - Order. In the First -Order a latent variable is measured by several indicators that can be measured directly, this is the model equation [13].

$$x = \Lambda_x \xi + \delta \tag{1}$$

With the covariance matrix $\boldsymbol{x}$ is written as a function θ and direpresentasi as $\Sigma(\theta)$

$$\Sigma(\theta) = \Lambda_x \Phi \Lambda_x^{'} + \Theta_\delta \tag{2}$$

Where x is the observation variables, Λ is a matrix loading factor, ξ is a latent variable, and δ is the measurement error matrix, Φ is the covariance matrix is latent variables, ξ and Θ_δ error covariance matrix for measurement δ

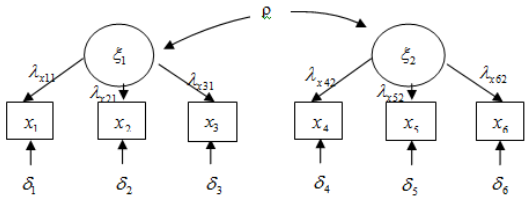

Figure 1. First - Order CFA

Bayes factor is an alternative Bayesian hypothesis test compared with the classical method. Classical hypothesis testing provides testing only for one hipoetesis (or model) as the initial hypothesis (H0) and determinationthe evidence against the hypothesis. One of the main problems is to choose the previous distribution (prior distribution). In most applications the model, researchers must assign a fixed value to the specified parameters. There are at least two reasons for doing this is to achieve the ability to identify the model and to obtain more meaningful interpretation.With Bayesian, this is equivalent to set a specific parameter to the value associated with probability. Fixed value is not specified as a parameter θ and estimates consist of the remaining free parameters in Λ, θ and ψ [16].

Bayesian approach based on bayes theorem, which that $p(x \mid \theta)p(\theta) = p(\theta \mid x)p(x)$ states the posterior distribution is obtained [16].

$$p(\theta \mid x) = \frac{p(\theta, x)}{p(x)} = \frac{p(x \mid \theta)p(\theta)}{p(x)} \tag{3}$$

or

$$p(\theta \mid x) \propto p(x \mid \theta)p(\theta) \tag{4}$$

For an observation data x and unknown parameters θ, the joint probability distribution $p(\theta, x)$ can be written as a multiplication of two density, ie prior distribution $p(\theta)$ and sampling distribution $p(x \mid \theta)$.

The Bayesian approach, CFA parameter estimation does not use the input variance covariance matrix of the data but only from observational data [17]. Bayesian estimation can be written as [17].

$$p(x, \theta \mid M) = p(x \mid \theta, M)\, p(\theta) = p(\theta \mid x, M)\, p(x \mid M)$$

where

M : CFA is an arbitrary shapes with unknown parameter vector ,

x : is the observation data by size

$p(\theta \mid M)$: is the prior distribution of θ at M the models ,

$p(x, \theta \mid M)$: is the joint probability distribution of x and θ at M condition the model is known

$p(\theta \mid x, M)$: is the probability distribution of the posterior .

$p(x \mid M)$ not dependent θ and to assume a predetermined x and constant, then

$$\log p(\theta \mid x, M) \propto \log p(x \mid \theta, M) + \log p(\theta)$$

If $x = (x_1, ..., x_n)$ the observation is a data matrix, $\Omega = (\xi_1, ..., \xi_n)$ a matrix of values latent factors, θ and is a vector parameter that includes the unknown element of Λ_x, Φ, and Θ_ε in the model . In the posterior analysis, x observation data is added to the matrix latent variables Ω and joint posterior distribution $[\theta, \Omega \mid x]$ generated by the Gibbs sampler algorithm. Gibbs Sampler is one way to simulate the value of a parameter with another condition parameters in a model. At iteration (j+1) to the present value of the $\Omega^{(j)}$, $\Theta_\delta^{(j)}$, $\Lambda^{(j)}$ and $\Phi^{(j)}$. [18]

i. Generate $\Omega^{(j+1)}$ of $p(\Omega \mid \Theta_\delta^{(j)}, \Lambda^{(j)}, \Phi^{(j)}, x)$

ii. Generate $\Theta_\delta{}^{(j+1)}$ of $p(\Theta_\delta \mid \Omega^{(j+1)}, \Lambda^{(j)}, \Phi^{(j)}, x)$

iii. Generate $\Lambda^{(j+1)}$ of $p(\Lambda \mid \Omega^{(j+1)}, \Theta_\delta^{(j+1)}, \Phi^{(j)}, x)$

iv. Generate $\Phi^{(j+1)}$ of $p(\Phi \mid \Omega^{(j+1)}, \Theta_\delta^{(j+1)}, \Lambda^{(j+1)}, x)$

Bayesian estimation requires the definition of prior distribution. Basically there are two types of prior distributions that is non - informative and informative priors [16]. Distribution of non - informative priors related to situations where the prior distribution does not have the population base. The distribution of non-informative prior are used when there is little information prior to distibusi prior minimal role in the posterior distribution. Resources for distibusi informative priors, can be obtained from distibusi one related data or subjective knowledge of experts. An informative prior distribution can have its own parameters called hyperparameters. One type of informative priors based on the conjugate prior distribution, is one which, when combined with the likelihood function resulting posterior distribution.

In this study used prior distribution is conjugate prior distribution [16][17]

$$\begin{aligned}
&\Theta_{\delta k} \sim InverseGamma[\alpha_{0\delta k}, \beta_{0\delta k}] \\
&[\Lambda_k \mid \Theta_{\delta k}] \sim Normal[\Lambda_{0k}, \Theta_{\delta k} H_{0xk}] \\
&\Phi \sim InverseWishart\ [R_0^{-1}, \rho_0] \\
&\xi \sim Multivariate\ Normal(0, \Phi)
\end{aligned} \tag{5}$$

Where $Gamma(\alpha, \beta)$ represents the gamma distribution with parameters $\alpha > 0$ and $\beta > 0$, Inverse Wishart [.,.]. Denotes the inverse Wishart distribution and the dimension r and $\alpha_{0\delta k}, \beta_{0\delta k}, \Lambda_{0k}, \rho_0$ positive definite matrix H_{0xk}, R_0 is hiperparameter the value assumed based on information from previous studies

To obtain settlement Bayesian estimation requires a numerical approach, the method of Markov Chain Monte Carlo (MCMC). MCMC method has been widely applied in various fields to solve a variety of problems. The algorithm that is often used in the MCMC method, namely the Metropolis - Hastings and Gibbs Sampler. In this study, the algorithm used is the Gibbs sampler. Gibbs Sampler is a technique to generate random variables from marginal distributions indirectly without having to calculate the density. By using the Gibbs sampler, a difficult calculation can be avoided [19]

2.3 Index

Determination of the index that is based on the BCFA are as follows [20]

$$I_R = X' F_l \times 100 \tag{6}$$

with,
$\boldsymbol{X}$: data indicator and$\boldsymbol{F}$: loading factor of latent variable

3. METHODOLOGY

The data used are primary and secondary data. Research location is in space postpartum Obstetrics Gynecology Hospital Dr. Soewandhi Surabaya. Samples were spontaneous postpartum maternal / induction and SC in the postpartum Obgyn Hospital Dr. Soewandhie taken by simple random sampling in the period July 2014 - October 2014 [12]. Physical Health Obstetrics Variable consists of 16 indicators, ie the frequency of eating (KFO1), protein consumption (KFO2), total sleep time per day (KFO3), smoke (KFO4) , age pregnancy first (KFO5), irregular menstruation (KFO6), SC Previous history (KFO7), Parity (KFO8), distance ages of children smallest (KFO9), lekore before and during pregnancy (KFO10), blood pressure (KFO11), vitamin/Fe (KFO12), disease during pregnancy (KFO13), pregnancy posterm (KFO14), history of miscarriage and stillbirth (KFO15) and drug beyond prescribing physician (KFO16) .

The following conceptual framework of Physical Health Obstetrics.

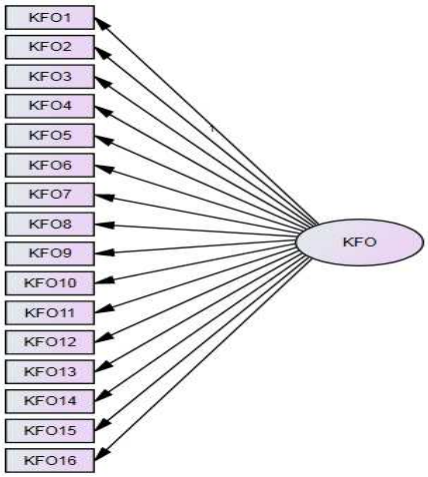

Figure 2. Conceptual Framework Research

4. RESULTS AND DISCUSSION

CFA covariance -based modeling requires multivariate normal distribution of data. This method will produce a good parameter estimates if the data meet the assumption of multivariate normal. Multivariate testing is normal to the following data [10][11]

H_0: Data multivariate normal distribution

H_1: Data not multivariate normal distribution

Table 1. Multivariate Testing Normal

Indicator	Min	Max	skew	c.r.	kurtosis	c.r.
KFO1	1.000	3.000	-.330	-.973	-.818	-1.203
KFO2	1.000	3.000	-.608	-1.791	-1.170	-1.723
KFO3	1.000	3.000	-.260	-.766	-.859	-1.265
KFO4	1.000	3.000	-1.278	-3.762	-.367	-.540
KFO5	1.000	3.000	-.886	-2.609	-.752	-1.106
KFO6	1.000	2.000	-1.041	-3.063	-.917	-1.350
KFO7	1.000	3.000	-2.266	-6.671	3.240	4.769
KFO8	1.000	3.000	-1.379	-4.058	.854	1.257
KFO9	1.000	3.000	-.202	-.596	-1.315	-1.936
KFO10	1.000	3.000	-2.141	-6.303	2.584	3.804
KFO11	1.000	3.000	-.944	-2.779	-.676	-.996
KFO12	1.000	3.000	-.297	-.873	-1.139	-1.676
KFO13	1.000	3.000	-.933	-2.747	-1.070	-1.574
KFO14	1.000	3.000	-.934	-2.749	-1.128	-1.660
KFO15	1.000	3.000	-2.408	-7.088	3.797	5.589
KFO16	1.000	3.000	.000	.000	-2.000	-2.944
Multivariate					69.856	10.495

Table 1 shows that the value of 10 495 CR Multivarite located outside of the value of -1.96 to 1.96, then the multivariate normal distribution data. Furthermore, use Bayesian CFA with the following results.

Early iterations

Bayesian estimation difference with Maximum Likelihood estimates lies in the addition of prior distribution. Prior distribution plays a very important because it is used in the formation of the posterior distribution. Formation of prior distribution using conjugate priors. Conjugate prior distribution requires a definition of value hiperparameter in its formation. Gradually hiperparameter value determination was based on previous studies that refer to the results of the study (Lee, 2012), and the last stage is the trial error. Prior distributions were used in this study for the initial iteration refers to the results of research is [18].

- $[(\Lambda_X|\boldsymbol{\theta}_\delta)]\sim N(0;\theta)$
- $\boldsymbol{\theta}\sim$Invers Gamma (9,4)
- $\xi\sim MN(0,\boldsymbol{\Phi})$dengan$\boldsymbol{\Phi}\sim IW\left(\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix},5\right)$

Table 2. Parameter Estimation Using Bayesian Early iterations

Laten Variable	Indicator	Loading Factor	2.50%	median	97.50%	information
KFO	KFO1	-0.013	-0.473	-0.014	0.451	Not Significant
	KFO2	0.359	-0.197	0.359	0.934	Not Significant
	KFO3	0.467	0.001	0.464	0.947	Significant
	KFO4	1.000*				Significant
	KFO5	0.585	0.070	0.578	1.137	Significant
	KFO6	0.201	-0.220	0.197	0.638	Not Significant
	KFO7	-0.289	-0.789	-0.288	0.197	Not Significant
	KFO8	0.152	-0.324	0.148	0.640	Not Significant
	KFO9	-0.152	-0.675	-0.153	0.380	Not Significant
	KFO10	0.468	-0.034	0.462	1.020	Not Significant
	KFO11	1.035	0.538	1.030	1.565	Significant
	KFO12	0.247	-0.204	0.245	0.716	Not Significant
	KFO13	1.307	0.780	1.295	1.895	Significant
	KFO14	0.047	-0.551	0.048	0.643	Not Significant
	KFO15	0.308	-0.246	0.304	0.867	Not Significant
	KFO16	1.169	0.545	1.153	1.838	Significant

Seen that in Table 2, many variables that are not significant indicator in measuring latent variables, because the value of the indicator variable loading factor of less than 0.50 and the value of the posterior probability interval 2.5 % to 97.5 % still contains a zero value, so these indicators are still not significant in measuring latency. Furthermore, the change in value hiperparameter the prior distribution by utilizing the results of the initial estimate in order to obtain significant results on all indicators.

Second iteration, Prior distribution used in the second iteration refers to the results of the initial iteration is.

- $[(\Lambda_X|\boldsymbol{\theta}_\delta)]\sim N(0.4;5\theta)$
- $\boldsymbol{\theta}\sim$Invers Gamma (9,4)
- $\xi\sim MN(0,\boldsymbol{\Phi})$dengan$\boldsymbol{\Phi}\sim IW\left(\begin{bmatrix}3&0&0\\0&3&0\\0&0&3\end{bmatrix},40\right)$

Table 3. Parameter Estimation Using Bayesian Second Iteration

Laten Variable	Indicator	Loading Factor	2.50%	median	97.50%	information
KFO	KFO1	0.358	-0.061	0.356	0.785	Not Significant
	KFO2	0.703	0.223	0.702	1.190	Significant
	KFO3	0.594	0.171	0.593	1.010	Significant
	KFO4	1.000*				Significant
	KFO5	0.771	0.308	0.772	1.218	Significant
	KFO6	0.439	0.051	0.439	0.821	Not Significant
	KFO7	0.178	-0.276	0.173	0.654	Not Significant
	KFO8	0.439	0.009	0.439	0.865	Not Significant
	KFO9	0.265	-0.230	0.266	0.774	Not Significant
	KFO10	0.654	0.199	0.652	1.109	Significant
	KFO11	0.707	0.217	0.709	1.177	Significant
	KFO12	0.589	0.207	0.590	0.973	Significant
	KFO13	1.050	0.546	1.055	1.529	Significant
	KFO14	0.255	-0.290	0.252	0.793	Not Significant
	KFO15	0.4031	-0.0752	0.4056	0.8808	Not Significant
	KFO16	0.9225	0.375	0.9278	1.452	Significant

Seen that in Table 3, many variables that are not significant indicator in measuring latent variables , because the value of the indicator variable loading factor of less than 0.50 and the value of the posterior probability interval 2.5 % to 97.5 % still contains a zero value , so these indicators are still not significant in measuring latency . Furthermore, the change in value hiperparameter the prior distribution by utilizing the results of the initial estimate in order to obtain significant results on all indicators. Indicator value is less than 0.5 but the value of the posterior probability interval does not contain the value zero indicates that an indicator variable has a relatively small effect on the latent variables.

Third iteration, Prior distribution used in the third iteration refers to the results of the second iteration is.

- $[(\Lambda_X|\boldsymbol{\theta}_\delta)]\sim N(0.5; 5\theta)$
- $\boldsymbol{\theta}\sim$Invers Gamma (9,4)
- $\xi\sim MN(0, \boldsymbol{\Phi})$dengan $\boldsymbol{\Phi}\sim IW\left(\begin{bmatrix}3 & 0 & 0\\ 0 & 3 & 0\\ 0 & 0 & 3\end{bmatrix}, 40\right)$

Table 4. Parameter Estimation Using Bayesian Third Iteration

Laten Variable	Indicator	Loading Factor	2.50%	median	97.50%	information
KFO	KFO1	0.358	-0.061	0.356	0.785	Not Significant
	KFO2	0.703	0.223	0.702	1.190	Significant
	KFO3	0.594	0.171	0.593	1.010	Significant
	KFO4	1.000*				Significant
	KFO5	0.771	0.308	0.772	1.218	Significant
	KFO6	0.439	0.051	0.439	0.821	Significant
	KFO7	0.178	-0.276	0.173	0.654	Not Significant
	KFO8	0.439	0.009	0.439	0.865	Significant
	KFO9	0.265	-0.230	0.266	0.774	Not Significant
	KFO10	0.654	0.199	0.652	1.109	Significant
	KFO11	0.707	0.217	0.709	1.177	Significant
	KFO12	0.589	0.207	0.590	0.973	Significant
	KFO13	1.050	0.546	1.055	1.529	Significant
	KFO14	0.255	-0.290	0.252	0.793	Not Significant
	KFO15	0.467	-0.030	0.469	0.961	Not Significant
	KFO16	0.971	0.400	0.976	1.524	Significant

Seen that in Table 4, there are several variables that are not significant indicator in measuring latent variables, because he value of the posterior probability interval 2.5 % to 97.5 % still contains the value zero , so that these indicators are still not significant in measuring latency. Furthermore, the change in value hiperparameter the prior distribution by utilizing the results of the initial estimate in order to obtain significant results on all indicators.

Fourth iteration, Prior distribution used in the fourth iteration refers to the results of the third iteration is .

- $[(\Lambda_X|\boldsymbol{\theta}_\delta)]\sim N(0.6; 5\theta)$
- $\boldsymbol{\theta}\sim$Invers Gamma (9,4)
- $\xi\sim MN(0, \boldsymbol{\Phi})$dengan $\boldsymbol{\Phi}\sim IW\left(\begin{bmatrix}2 & 0 & 0\\ 0 & 2 & 0\\ 0 & 0 & 2\end{bmatrix}, 40\right)$

Table 5. Parameter Estimation Using Bayesian Fourth Iteration

Laten Variable	Indicator	Loading Factor	2.50%	median	97.50%	information
KFO	KFO1	0.475	0.028	0.472	0.930	Significant
	KFO2	0.819	0.308	0.819	1.328	Significant
	KFO3	0.689	0.236	0.688	1.132	Significant
	KFO4	1.000*				Significant
	KFO5	0.875	0.380	0.876	1.351	Significant
	KFO6	0.534	0.115	0.535	0.937	Significant
	KFO7	0.296	-0.194	0.291	0.802	Not Significant
	KFO8	0.551	0.093	0.552	1.005	Significant
	KFO9	0.379	-0.157	0.378	0.924	Not Significant
	KFO10	0.756	0.271	0.755	1.243	Significant
	KFO11	0.778	0.257	0.780	1.279	Significant
	KFO12	0.693	0.288	0.694	1.104	Significant
	KFO13	1.138	0.596	1.142	1.655	Significant
	KFO14	0.346	-0.241	0.344	0.927	Not Significant
	KFO15	0.565	0.036	0.568	1.092	Not Significant
	KFO16	1.054	0.445	1.060	1.643	Significant

CFA model parameter estimation is done using a second iteration WinBUGS program assistance 1.4.3. By iterating as many as 10,000 times, parameter estimation process reaches burn in the first iteration. Seen that in Table 5, there are four variables were not significant indicator in measuring latent variables, namely the latent variables KFO with each indicator KFO7, KFO9, KFO14, and KFO15, because the value of the indicator variable loading factor of less than 0.50 as well as the value of the posterior probability interval 2.5% to 97.5% still contains a value of zero, so that these indicators are still not significant in measuring latency. Furthermore, the change in value hiperparameter the prior distribution by utilizing the results of the initial estimate in order to obtain significant results on all indicators. Indicator value is less than 0.5 but the value of the posterior probability interval does not contain the value zero indicates that an indicator variable has a relatively small effect on the latent variables.

Fifth iteration

Prior distribution used in the fifth iteration refers to the results of the fourth iteration is.

- $[(\Lambda_X|\boldsymbol{\theta}_\delta)]\sim N(0.9; 6\theta)$
- $\boldsymbol{\theta}\sim$Invers Gamma (9,4)
- $\xi\sim MN(0, \boldsymbol{\Phi})$dengan $\boldsymbol{\Phi}\sim IW\left(\begin{bmatrix}8 & 0 & 0\\ 0 & 8 & 0\\ 0 & 0 & 8\end{bmatrix}, 40\right)$

Table 6. Parameter Estimation Using Bayesian Fifth Iteration

Laten Variable	Indicator	Loading Factor	2.50%	median	97.50%	information
KFO	KFO1	0.703	0.286	0.701	1.118	Significant
	KFO2	1.016	0.555	1.015	1.463	Significant
	KFO3	0.845	0.430	0.844	1.254	Significant
	KFO4	1.000*				Significant
	KFO5	0.875	0.380	0.876	1.351	Significant
	KFO6	0.534	0.115	0.535	0.937	Significant
	KFO7	0.296	0.194	0.291	0.802	Significant
	KFO8	0.551	0.093	0.552	1.005	Significant
	KFO9	0.379	0.157	0.378	0.924	Significant
	KFO10	0.756	0.271	0.755	1.243	Significant
	KFO11	0.778	0.257	0.780	1.279	Significant
	KFO12	0.693	0.288	0.694	1.104	Significant
	KFO13	1.138	0.596	1.142	1.655	Significant
	KFO14	0.346	0.241	0.344	0.927	Significant
	KFO15	0.565	0.036	0.568	1.092	Significant
	KFO16	1.054	0.445	1.060	1.643	Significant

CFA model parameter estimation is done using a second iteration WinBUGS program assistance 1.4.3. By iterating as many as 10,000 times, parameter estimation process reaches burn in the first iteration. Table 6 shows the loading factor values greater than 0.5 and the value of the posterior probability interval 2.5 % to 97.5 % does not contain the value zero, which means the KFO latent variables can be measured through 16 indicators.

Interval values can be interpreted a probability parameter lies within a certain interval with the data requirements such as the observation data is of 100 (1-α) %. Suppose the interval for eating frequency indicator (KFO1) is between the value of 0.2859 to 1.118. It shows the probability of parameter values (loading factor) is in the interval [0.2859; 1.118] was 97.5%. Further modeling BCFA presented in Figure below.

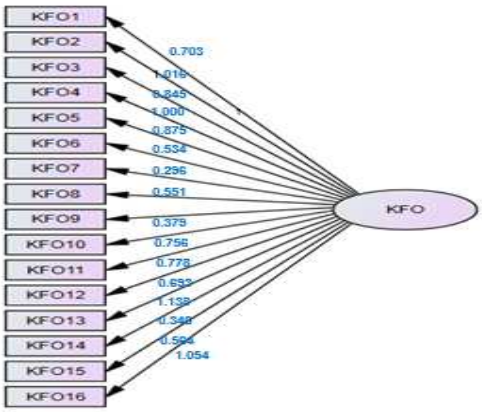

Figure 3. Measurement Model of Physical Health Obstetrics

4.3 . Physical Health ObstetricsIndex

To obtain an index KFO first sought first latent variable factor score KFO, then according to the equation (3) is produced KFO Index are presented in the following table.

Table 7. Patient Physical Health ObstetricsIndex

Obs	Score Factor	Indeks KFO	Code IKFO	Obs	Score Factor	Indeks KFO	Code IKFO	Obs	Score Factor	Indeks KFO	Code IKFO
1	0.252	82.579	2	19	0.156	51.170	1	37	0.007	2.330	1
2	0.669	218.945	3	20	0.464	151.645	3	38	0.551	180.273	3
3	0.506	165.616	3	21	0.003	1.007	1	39	0.541	176.969	3
4	0.108	35.466	1	22	0.247	80.845	2	40	0.001	0.489	1
5	0.162	52.904	1	23	0.211	69.034	1	41	0.000	0.106	1
6	0.552	180.633	3	24	0.643	210.209	3	42	0.769	251.531	3
7	0.117	38.116	1	25	0.629	205.629	3	43	0.440	143.826	3
8	0.203	66.318	1	26	0.269	87.944	2	44	0.466	152.594	3
9	0.442	144.644	3	27	0.002	0.795	1	45	0.073	23.786	1
10	0.724	236.972	3	28	0.318	104.041	2	46	0.248	81.008	2
11	0.465	152.103	3	29	0.108	35.269	1	47	0.665	217.702	3
12	0.578	189.139	3	30	0.006	1.914	1	48	0.333	108.818	2
13	0.001	0.363	1	31	0.316	103.256	2	49	0.008	2.773	1
14	0.000	0.110	1	32	0.271	88.501	2	50	0.527	172.486	3
15	0.536	175.300	3	33	0.370	121.120	3	51	0.220	72.109	1
16	0.054	17.821	1	34	0.617	201.736	3	52	0.209	68.445	1
17	0.138	45.117	1	35	0.379	123.868	3				
18	0.033	10.957	1	36	0.286	93.670	2				
IKFO < 78.9 = 1 (42.3%), 78.9 < IKFO < 121.1 = 2 (17.3%), IKFO > 121.1 = 3 (40.4%)											

Table 7 shows that KFO index of 52 observations based on the 95% confidence interval can be IKFO < 78.9 = 1, 78.9 < IKFO < 121.1 = 2, and IKFO > 121.1 = 3. KFO index of 52 observations can be categorized into three namely be considered a high of 40.4 % , 17.3 % moderate and 42.3 % lower .

5. CONCLUSION

The results showed that the BCFA approach measurement model of obstetric physical health is fit model , and the indicator is dominant in shaping the successive reproductive health is the disease during pregnancy (KFO13), drug beyond prescribing physician (KFO16),protein consumption (KFO2), smoke (KFO4), age pregnancy first (KFO5), total sleep time per day (KFO3), blood pressure (KFO11), lekore before and during pregnancy (KFO10), frequency of eating (KFO1), vitamin / Fe (KFO12), history of miscarriage and stillbirth (KFO15), Parity (KFO8), irregular menstruation (KFO6), distance ages of children smallest (KFO9), pregnancy posterm (KFO14) and SC Previous history (KFO7). KFO index of 52 observations based on the 95% confidence interval can be categorized into three namely high of 40.4 % , 17.3 % moderate and 42.3 % lower .

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