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IMPLEMENTATION OF PLS-PM IN KNOWING THE FACTORS THAT INFLUENCE THE INCIDENCE OF TYPHOID FEVER IN PATIENTS IN ANUTAPURA PALU HOSPITAL

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ABSTRACT

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Typhoid fever is a multifactorial disease that has factors that can have an impact, including individual characteristics, maternal knowledge, hygiene, and nutritional status. Data on the incidence of typhoid fever involves many variables that cannot be examined directly (latent variables). This study used secondary data obtained from the medical records of typhoid fever patients at Anutapura Palu Hospital in 2023. One of the statistical methods that can be used to explain the relationship between indicators and latent variables is Partial Least Squares-Path Modeling (PLS-PM). Therefore, this study aims to model the influence of individual characteristics, maternal knowledge, hygiene, and nutritional status on the incidence of typhoid fever in patients at Anutapura Palu Hospital using PLS-PM analysis. The results of the PLS-PM analysis show that individual characteristics and nutritional status have a direct effect on the clinical images, while maternal knowledge and hygiene indirectly affect the clinical images through nutritional status, with a coefficient of determination of 0.828. So, it can be said that nutritional status is able to mediate between individual characteristics, maternal knowledge, and hygiene with the clinical images of typhoid fever.

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1. INTRODUCTION

Typhoid fever is a disease that is found in most communities with low standards of living and hygiene, tends to increase, and occurs locally [1]. Typhoid fever is an acute infectious disease of the small intestine with characteristic signs and symptoms of abdominal pain, rash, and fever [2]. Typhoid fever is also a multifactorial disease, where the infectious factors can come from various factors such as age, gender, environmental hygiene, occupation, level of education, and personal hygiene, as well as where the patient lives [3].

Typhoid fever in Indonesia is endemic and often occurs in large cities. About 350 to 810 people per 100,000 population suffer from typhoid fever, with an incidence of 1.6%, and ranks 5th among infectious diseases that occur in all age groups in Indonesia (6%), and ranks 15th as a cause of death at all ages (1.6%) [4]. In accordance with the Health Profile of Central Sulawesi Province from 2020 to 2022, it was found that the number of typhoid fever cases continued to increase, from 1,984 cases to 2,026 cases in 2022.

The high incidence of typhoid fever is inseparable from the risk factors that cause typhoid fever. Some risk factors for typhoid fever are closely related to nail hygiene, hand washing habits, children's snacking behavior, and maternal knowledge [5]. Typhoid fever is a multifactorial disease that causes a continuous increase in incidence. Multifactorial means having factors that can have an impact, including personal hygiene and environmental sanitation [6].

A commonly used method to test the relationship between variables is linear regression [7]. However, when the variables used are variables that cannot necessarily be observed directly (latent variables), the use of multiple regression models becomes less appropriate. Such is the case with typhoid fever incidence data, which includes many latent variables. One multivariate statistical method that can be used to explain these complex relationships is the Partial Least Squares-Path Modeling (PLS-PM) model [8].

PLS was developed by Herman Wold in 1996 and became the basic model in 1977. Some of the capabilities of PLS-PM make it a more flexible and powerful method, without assumptions about the distribution of indicators and the type of data scale in the form of nominal, ordinal, or interval, and the use of small samples [9]. PLS-PM is a multivariate analysis method that focuses on the relationship between latent variables and observable variables. PLS-PM aims to develop theory, so it does not require a strong understanding of theory, and can measure the accuracy of prediction parameters reflected in the coefficient of determination (R^2) [10].

Research using the PLS-PM method has been conducted previously in analyzing factors that affect customer loyalty [12]. It has also been conducted in predicting environmental issue factors on environmental management control systems [16]. But in previous studies, no one has applied it in analyzing the incidence of typhoid fever

This study aims to determine the factors that influence the incidence of typhoid fever in patients at Anutapura Palu Hospital using the Partial Least Squares-Path Modeling (PLS-PM) method. The results of this study are expected to be an input for making policies to prevent typhoid fever.

2. RESEARCH METHODS

2.1 Data Collection

The data used in this study is in the form of secondary data obtained from medical records with a sample of 55 typhoid fever patients at Anutapura Palu Hospital in 2023. The variables used were 5 latent variables and 17 indicators forming the latent variables. The determination of the sample size is based on the theory put forward by [11] that using only 20 samples can conclude that the PLS procedure can run well.

2.2 Variable Definition

This research consists of endogenous variables and exogenous variables. The endogenous latent variables used are nutritional status variables and clinical images. Meanwhile, the exogenous latent variables used in this study are individual characteristics, maternal knowledge, and hygiene. The indicators used to measure latent variables can be seen in **Table 1**.

Table 1. Indicator of Latent Variable

Latent Variable	Indicator	
Nutritional Status (η_1)	Y_{11}	Dietary Habit
	Y_{21}	Food Portion
	Y_{31}	Types of Drinks
Clinical Images (η_2)	Y_{12}	Duration of Fever
	Y_{22}	Vomit
	Y_{32}	Stomach Ache
	Y_{42}	Cough
	Y_{52}	Indigestion
Individual Characteristics (ξ_1)	X_{11}	Age
	X_{21}	Gender
	X_{31}	School Status
Maternal Knowledge (ξ_2)	X_{12}	Understanding of Disease
	X_{22}	Understanding of Treatment
	X_{32}	Understanding of Care
	X_{42}	Understanding of Nutrition
Hygiene (ξ_3)	X_{13}	Body
	X_{23}	Environment

Table 1 shows several variables and indicators used in this study. Where the endogenous latent variable consists of 2 variables. The nutritional status variable (η_1) is composed of 3 indicators, namely dietary habit (Y_{11}), food portion (Y_{21}), and types of drinks (Y_{31}). In addition, the clinical images (η_2) variable also consists of 5 indicators, namely duration of fever (Y_{12}), vomit (Y_{22}), stomach ache (Y_{32}), cough (Y_{42}), and indigestion (Y_{52}). Meanwhile, the exogenous variable consists of 3 variables, namely, Individual Characteristics (ξ_1), Maternal Knowledge (ξ_2), and Hygiene (ξ_3) which in each variable also has several forming indicators.

Individual characteristics are one of the factors causing the incidence of typhoid fever. According to the high incidence of typhoid fever, it is inseparable from risk factors that predispose to typhoid fever. One of the risk factors for typhoid fever is maternal knowledge. The increasing incidence of typhoid fever is also because typhoid fever is a multifactorial disease, which means that it has factors that can have an impact, including personal hygiene and sanitation **[5]**. Nutritional status is one of the factors that influence the incidence of typhoid fever **[17]**.

2.3 Analytical Approach

This study uses the Partial Least Squares-Path Modeling (PLS-PM) reflective model method, by applying the Confirmatory Factor Analysis (CFA) approach using the help of RStudio and SmartPLS software. The stages of the analysis carried out are as follows. The stages of the analysis carried out can be seen in **Figure 1**.

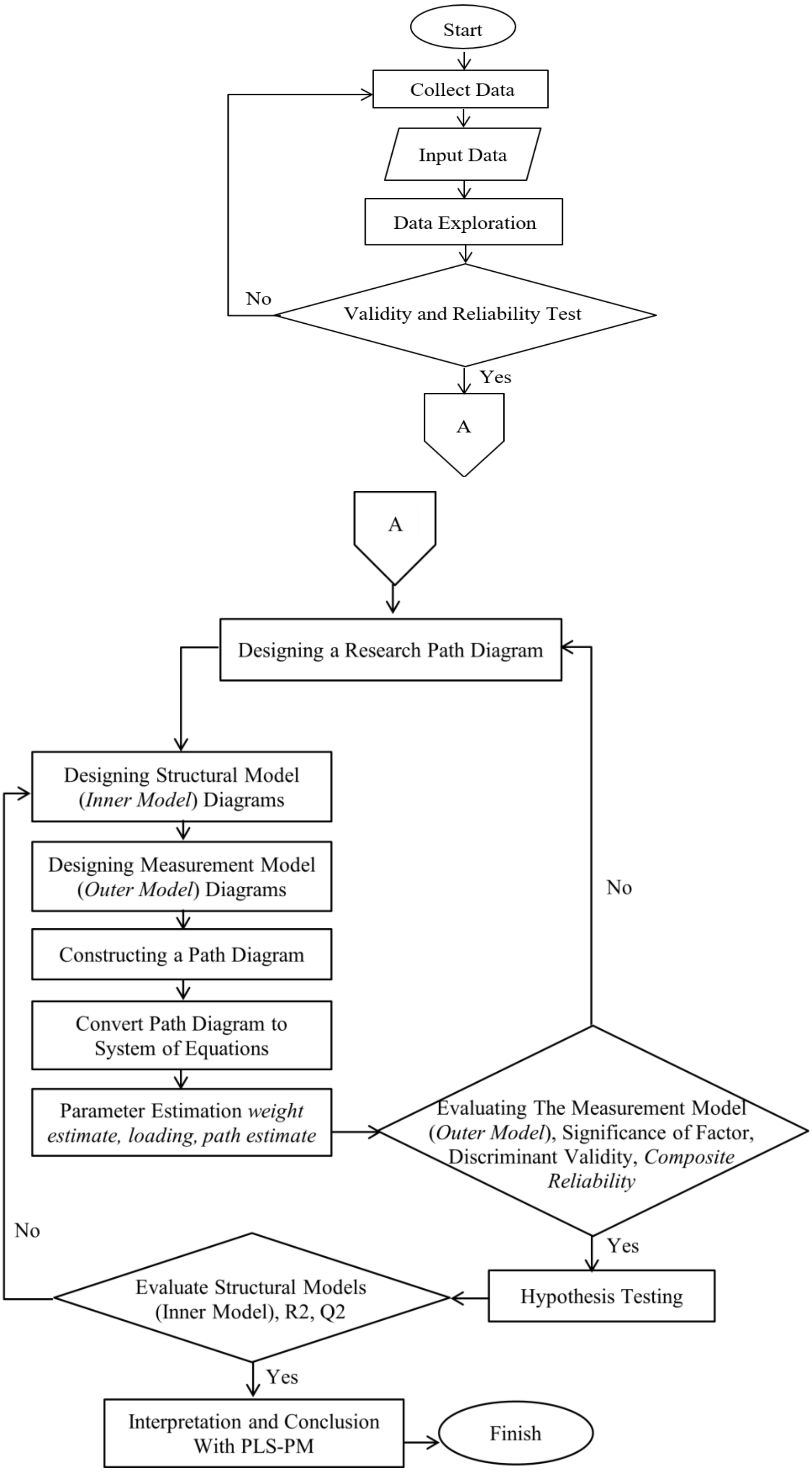

Figure 1. Research Flow Diagram

Figure 1 shows the stages of data analysis in this study. there are several stages of the data analysis process using PLS-PM analysis. the stages of PLS-PM analysis include data entry, data exploration, checking research instruments, and entering the PLS-PM analysis stage.

2.3.1 Partial Least Squares (PLS)

Partial Least Squares (PLS) is a method that is more suitable for prediction purposes. In this method, the latent variable is the result of a linear combination of its manifest variables, making it easier to predict the value of the latent variable and also predict the latent variable it affects [12]. Latent variables are essential constructs in a field of science, constructed based on theory or hypothesis [20]. PLS is more suitable for reflective measurement models where indicator variables are considered as effects of the underlying construct [9]. These variables are classified into two categories: endogenous (dependent) and exogenous (independent) variables [18].

2.3.2 Partial Least Square (PLS) Assumptions

In PLS, no particular distribution is assumed in parameter estimation, so parametric techniques for testing parameter significance are not required. The prediction measures underlying the evaluation of PLS models are nonparametric [12]. PLS is one of the most powerful methods and can be used on data with different scales without requiring assumptions and without using large samples. Although not knowing the data distribution is a weakness of PLS, it cannot obtain statistical significance. However, this weakness can be overcome by using resampling or bootstrap methods [13].

2.3.3 Path Diagram

After designing the inner model and outer model, understanding it will be easier through representation in the form of a path diagram. The path diagram of the results of designing the measurement model and structural model can be seen in **Figure 2** [12].

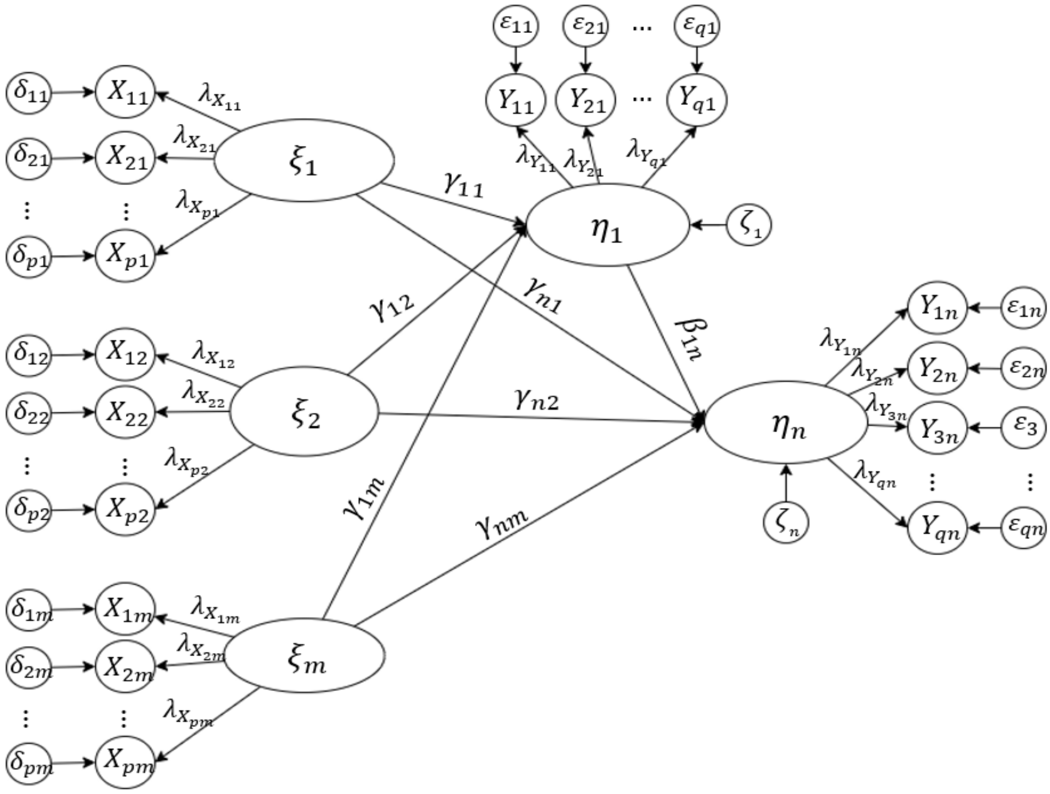

Figure 2. PLS Path Diagram Example

Figure 2 is an example of a path diagram. It can be seen that there are 2 types of variables used, namely endogenous latent variables and exogenous latent variables. Besides that, it is also seen that each endogenous latent variable and exogenous latent variable has a variable-forming indicator, and there is an error in each indicator.

Where:
ξ : exogenous latent variable
η : endogenous latent variable
X : exogenous manifest variable
Y : endogenous manifest variable
λ_x : *loading factor* of exogenous latent variable
λ_y : *loading factor* of endogenous latent variable
β : coefficient of influence between endogenous latent variable
γ : coefficient of influence of exogenous latent variable on endogenous latent variable
ζ : model error
δ : measurement error on the manifest variable for the exogenous latent variable
ε : measurement error on the manifest variable for the endogenous latent variable

2.3.4 Measurement Model (*Outer Model*)

The outer model uses constructs that represent the relationship between latent variables and their indicators. The measurement model design includes models that reflect or are formed based on previous empirical research or theory-based theory [14]. The model that explains the latent variables that are affected or reflect their indicators is the reflective indicator model. The following is the indicator model equation for exogenous and endogenous variables [9].

$$\boldsymbol{X}_{(p\times1)} = \boldsymbol{\lambda}_{X_{(p\times m)}}\boldsymbol{\xi}_{(m\times1)} + \boldsymbol{\delta}_{(q\times1)} \tag{1}$$

$$\boldsymbol{Y}_{(q\times1)} = \boldsymbol{\lambda}_{Y_{(q\times n)}}\boldsymbol{\eta}_{(n\times1)} + \boldsymbol{\varepsilon}_{(q\times1)} \tag{2}$$

Where:
$\boldsymbol{X}$: vector variables manifesting exogenous
$\boldsymbol{Y}$: vector variables manifesting endogenous
$\boldsymbol{\lambda}_X$: loading matrix describing the relationship between indicators and exogenous variables
$\boldsymbol{\lambda}_Y$: loading matrix describing the relationship between indicators and endogenous variables
$\boldsymbol{\xi}$: vector of exogenous latent variables
$\boldsymbol{\delta}$: vector of measurement errors on indicators of exogenous latent variables
$\boldsymbol{\eta}$: vector of endogenous latent variables
$\boldsymbol{\varepsilon}$: vector of measurement errors on indicators of endogenous latent variables
p : number of indicators of exogenous variables
q : number of indicators of endogenous variables
m : number of exogenous variables
n : number of endogenous variables

2.3.5 Structural Model (*Inner Model*)

The inner model shows the relationship between latent variables. Analysis of relationship patterns in the inner model is done using path analysis. The structural model equation is described as follows [9].

$$\boldsymbol{\eta}_{(n\times1)} = \boldsymbol{B}_{(n\times n)}\boldsymbol{\eta}_{(n\times1)} + \boldsymbol{\Upsilon}_{(n\times m)}\boldsymbol{\xi}_{(m\times1)} + \boldsymbol{\zeta}_{(n\times1)} \tag{3}$$

Where:
$\boldsymbol{\eta}$: vector of endogenous latent variables
$\boldsymbol{\beta}$: matrix of influence coefficients between endogenous latent variables
$\boldsymbol{\gamma}$: matrix of path coefficients connecting exogenous latent variables with endogenous latent variables
$\boldsymbol{\xi}$: vector of exogenous latent variables
$\boldsymbol{\zeta}$: vector of structural errors
m : number of exogenous variables
n : number of endogenous variables

2.3.6 Parameter Estimation

There are three types of parameter estimation in PLS. The first type is the *weight estimate*, which is used to obtain latent values. The second type is estimating paths that connect latent variables (*path coefficients*) and between latent variables and their indicators (*loadings*). The third type concerns mean values and parameter assignments (constant regression values) for indicators and latent variables. The least squares method is used for parameter estimation in PLS. The calculation is done through iteration, where PLS uses a three-step iteration process so that each iteration produces an estimated value **[12]**.

2.3.7 Evaluate Models

The PLS evaluation model is based on nonparametric measurements. There are two model evaluations in PLS, namely **[12]**.

1. Measurement Model (*Outer Model*)

Convergent validity indicates that the indicators of a latent variable must have a high correlation. In PLS using reflective indicators, convergent validity can be assessed through the *loading factor* score (correlation between indicators and latent variables). The *loading factor* score is expected to have a value of > 0.5, but it is better if the value is > 0.7 **[11]**. The measure of discriminant validity for reflective indicators is based on the cross-loading of the indicator with the corresponding latent variable. Validity is said to be fulfilled if the cross-loading value of each indicator on the corresponding latent variable is greater than the cross-loading values on other latent variables. In addition, there is another method in discriminant validity, namely by looking at the Average Variance Extracted (AVE) score of each latent variable. If the AVE variable has a value ≥ 0.5, it can be said to have a good discriminant value **[12]**.

2. Structural Model (*Inner Model*)

The relationship between latent variables formed by the substance of the theory is described by a structural model, also known as an internal model **[19]**. The *goodness of fit* of the model is measured by the dependent latent variable R^2. In the structural model, the predicted significance value $Q_{squared}$ is used to evaluate the quality of the observation values obtained by the model and its parameter estimates. The model is said to have relevant predictions if the $Q_{squared}$ score > 0, conversely, if the $Q_{squared}$ value ≤ 0 indicates that the equation does not have relevant predictions **[12]**.

2.3.8 Hypothesis Testing

1. Hypothesis in the *outer model*

H_0 : $\lambda_k = 0$ (The parameter of the k^{th} indicator is not significant)

H_1 : $\lambda_k \neq 0$ (The parameter of the k^{th} indicator is significant)

The test statistics used can be seen in **Equation (4)**.

$$t_{count} = \frac{\hat{\lambda}_k}{SE(\hat{\lambda}_k)} \tag{4}$$

2. Hypothesis in the *inner model*

a. The effect of exogenous latent variables on endogenous latent variables.

H_0 : $\gamma_j = 0$ (The parameter of the j^{th} exogenous variable is not significant)

H_1 : $\gamma_j \neq 0$ (The parameter of the j^{th} exogenous variable is significant)

b. The effect of endogenous latent variables on other endogenous latent variables.

$H_0 : \beta_i = 0$ (The parameter of the i^th^ endogenous variable is not significant)

$H_1 : \beta_i \neq 0$ (The parameter of the i^th^ endogenous variable is significant)

The test statistics used can be seen in the Equation (5).

$$t_{count} = \frac{\hat{\gamma}_k}{SE(\hat{\gamma}_k)} \tag{5}$$

In both hypotheses above, conclusions are drawn by comparing the t_{count} and t_{table} scores at the significance level α. If $t_{count} > t_{table}$ then reject H_0. In addition, it can also be used by looking at the *p-value* and α value. Reject H_0 if the *p-value* < α [14].

3. RESULTS AND DISCUSSION

3.1 Research Instrument Test

Instrument testing is used to check the validity and reliability of the measuring instrument used. Research results must be valid and reliable through the use of valid and reliable instruments in data collection. The tests used to test the research instrument are the validity test and the reliability test. The validity test helps determine whether the questionnaire is able to measure what we want to measure or not. One way to find out which indicators are valid and which are not is to look at the correlation value [15]. The validity test results obtained are shown in Table 2.

Table 2. Validity Test Results

Variable	Indicator	*Correlation*	Information
Nutritional Status ($\boldsymbol{\eta_1}$)	Y_{11}	0.78	Valid
	Y_{21}	0.83	Valid
	Y_{31}	0.73	Valid
Clinical Images ($\boldsymbol{\eta_2}$)	Y_{12}	0.75	Valid
	Y_{22}	0.73	Valid
	Y_{32}	0.79	Valid
	Y_{42}	0.79	Valid
	Y_{52}	0.53	Valid
Individual Characteristics ($\boldsymbol{\xi_1}$)	X_{11}	0.74	Valid
	X_{21}	0.67	Valid
	X_{31}	0.76	Valid
Maternal Knowledge ($\boldsymbol{\xi_2}$)	X_{12}	0.58	Valid
	X_{22}	0.59	Valid
	X_{32}	0.51	Valid
	X_{42}	0.66	Valid
Hygiene ($\boldsymbol{\xi_3}$)	X_{13}	0.63	Valid
	X_{23}	0.68	Valid

Based on the validity test results in Table 2, there are 17 indicators. From the validity test results, it can be seen that the correlation value for each indicator is more than 0.3 [15], which means that it can be concluded that the 17 indicators used are all declared valid and can continue the reliability test. The results of the reliability test that have been carried out in this study and the results are shown in Table 3.

Table 3. Reliability Test Results

Variable	*Cronbach's Alpha*	Information
Nutritional Status ($\boldsymbol{\eta_1}$)	0.80	Reliable
Clinical Images ($\boldsymbol{\eta_2}$)	0.84	Reliable
Individual Characteristics ($\boldsymbol{\xi_1}$)	0.77	Reliable
Maternal Knowledge ($\boldsymbol{\xi_2}$)	0.65	Reliable
Hygiene ($\boldsymbol{\xi_3}$)	0.91	Reliable

Based on **Table 3**, the reliability test is carried out on indicators that have been declared valid. A questionnaire is declared reliable if the answers to the statements are always consistent. From the reliable test results above, the Cronbach's alpha value for each variable is 0.8, 0.84, 0.77, 0.65, and 0.91 or greater than 0.6 **[12]**, which means proving that all variables used are declared reliable.

3.2 Designing Structural Model Diagram and Measurement Model

The measurement model path diagram and structural model used in this study can be seen in **Figure 3**.

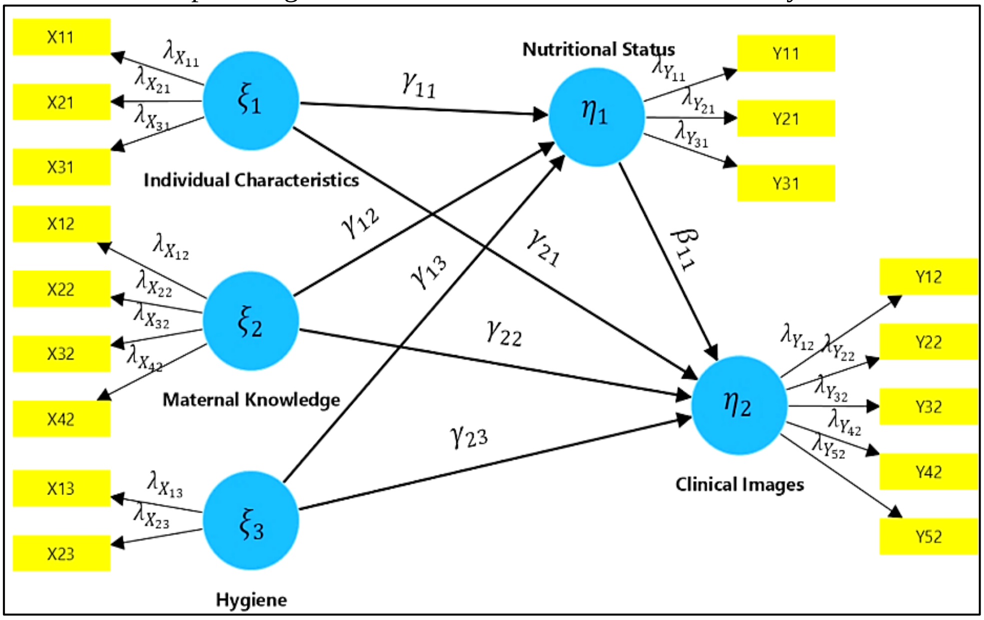

Figure 3. Research Path Diagram

In **Figure 3**, blue circles are latent variables and yellow rectangles are indicators of each latent variable. The relationship between exogenous latent variables and endogenous latent variables is shown with thicker colored arrows, with parameter coefficients indicated by the symbol γ, and the relationship between endogenous latent variables is shown with the symbol β. While the relationship between latent variables and each indicator is shown with thinner colored arrows, the parameter coefficient is indicated by the symbol λ.

3.3 Measurement Model (*Outer Model*) Evaluation

The *loading factor* values obtained are presented in **Table 4**.

Table 4. *Loading Factor* Values

Variable	Indicator	*Loading Factor*	Information
	Y_{11}	0.824	Valid
Nutritional Status ($\boldsymbol{\eta_1}$)	Y_{21}	0.873	Valid
	Y_{31}	0.835	Valid
Clinical Images ($\boldsymbol{\eta_2}$)	Y_{12}	0.78	Valid
	Y_{22}	0.828	Valid
	Y_{32}	0.825	Valid
	Y_{42}	0.827	Valid
	Y_{52}	0.647	Invalid
Individual Characteristics ($\boldsymbol{\xi_1}$)	X_{11}	0.774	Valid
	X_{21}	0.832	Valid
	X_{31}	0.877	Valid
Maternal Knowledge ($\boldsymbol{\xi_2}$)	X_{12}	0.706	Valid
	X_{22}	0.711	Valid
	X_{32}	0.639	Invalid
	X_{42}	0.735	Valid
Hygiene ($\boldsymbol{\xi_3}$)	X_{13}	0.95	Valid
	X_{23}	0.964	Valid

Table 4 shows that there are 2 indicators that have a loading factor value < 0.7, the indicators are Y_{52} and X_{32}, with a loading factor value of 0.647 and 0.639, respectively. To overcome invalid indicators, recalculation is carried out by removing invalid indicators from the model path diagram. So that the results are presented in **Table 5**.

Table 5. Modified *Loading Factor* Values

Variable	Indicator	*Loading Factor*	Information
Nutritional Status (η_1)	Y_{11}	0.823	Valid
	Y_{21}	0.873	Valid
	Y_{31}	0.836	Valid
Clinical Images (η_2)	Y_{12}	0.805	Valid
	Y_{22}	0.828	Valid
	Y_{32}	0.829	Valid
	Y_{42}	0.831	Valid
Individual Characteristics (ξ_1)	X_{11}	0.771	Valid
	X_{21}	0.834	Valid
	X_{31}	0.879	Valid
Maternal Knowledge (ξ_2)	X_{12}	0.741	Valid
	X_{22}	0.746	Valid
	X_{42}	0.761	Valid
Hygiene (ξ_3)	X_{13}	0.95	Valid
	X_{23}	0.964	Valid

In **Table 5**, it can be seen that when invalid indicators are removed from the model. The loading factor scores of all indicators have a loading factor score of more than 0.7. After convergent validity is met, it is necessary to proceed to the evaluation of discriminant validity. The crossloading values obtained are shown in **Table 6**.

Table 6. *Crossloading* Values

Indicator	Nutritional Status	Clinical Images	Individual Characteristics	Maternal Knowledge	Hygiene
Y_{11}	**0.829**	0.69	0.5	0.656	0.729
Y_{21}	**0.868**	0.758	0.793	0.697	0.424
Y_{31}	**0.834**	0.663	0.698	0.544	0.4
Y_{12}	0.73	**0.803**	0.671	0.498	0.421
Y_{22}	0.616	**0.828**	0.582	0.468	0.42
Y_{32}	0.662	**0.83**	0.76	0.569	0.46
Y_{42}	0.736	**0.832**	0.69	0.561	0.464
X_{11}	0.727	0.683	**0.774**	0.507	0.436
X_{21}	0.579	0.637	**0.832**	0.524	0.275
X_{31}	0.64	0.723	**0.877**	0.517	0.47
X_{12}	0.487	0.472	0.49	**0.741**	0.302
X_{22}	0.547	0.42	0.494	**0.745**	0.383
X_{42}	0.643	0.534	0.428	**0.762**	0.538
X_{13}	0.529	0.491	0.441	0.521	**0.951**
X_{23}	0.639	0.535	0.479	0.542	**0.963**

Based on **Table 6**, it can be seen that the latent variable is able to predict each indicator on the latent variable better, compared to indicators on other latent variables. So, it can be said that the indicators in this study have good discriminant validity.

3.4 Hypothesis Testing

The results of testing the direct and indirect influence hypotheses are obtained and can be seen in **Table 7**.

Table 7. Measurement Model Significance Test Value

Variable	Indicator	*Outer Loadings*		t_{count}	*p-value*
		Estimate	*Standard deviation*		
Nutritional Status ($\boldsymbol{\eta_1}$)	Y_{11}	0.823	0.052	15.801	0.000*
	Y_{21}	0.873	0.037	23.641	0.000*
	Y_{31}	0.836	0.052	16.071	0.000*
Clinical Images ($\boldsymbol{\eta_2}$)	Y_{12}	0.805	0.049	16.554	0.000*
	Y_{22}	0.828	0.056	14.863	0.000*
	Y_{32}	0.829	0.051	16.134	0.000*
	Y_{42}	0.831	0.06	13.946	0.000*
Individual Characteristics ($\boldsymbol{\xi_1}$)	X_{11}	0.771	0.066	11.752	0.000*
	X_{21}	0.834	0.067	12.382	0.000*
	X_{31}	0.879	0.054	16.337	0.000*
Maternal Knowledge ($\boldsymbol{\xi_2}$)	X_{12}	0.741	0.106	6.983	0.000*
	X_{22}	0.746	0.081	9.169	0.000*
	X_{42}	0.761	0.065	11.668	0.000*
Hygiene ($\boldsymbol{\xi_3}$)	X_{13}	0.95	0.027	34.667	0.000*
	X_{23}	0.964	0.016	61.927	0.000*

Based on Table 7, it can be seen that each indicator on the latent variable has a $t_{count} > t_{table}$ (2.021) and a *p-value* < α (0.05), so reject H_0. This shows that all indicator parameters are significant for each latent variable. Based on the loading factor value and standard error in Table 7, a mathematical equation model of the measurement model (outer model) is formed on the exogenous latent variable indicators and on the endogenous latent variable indicators.

Table 8. Direct Effect Significance Test

Variable	*Total Effect*		t_{count}	*p-value*
	Estimate	*Standard deviation*		
Individual Characteristics ($\boldsymbol{\xi_1}$)	0.674	0.104	6.509	0.000*
Maternal Knowledge($\boldsymbol{\xi_2}$)	0.148	0.114	1.291	0.2
Hygiene ($\boldsymbol{\xi_3}$)	0.133	0.09	1.477	0.143
Clinical Images ($\boldsymbol{\eta_1}$)	0.475	0.218	2.175	0.032*

Based on Table 8, it can be seen that there are two exogenous variables that have a *p-value* > α (0.05). So, it fails to reject H_0 which means that the variables of maternal knowledge and hygiene do not directly affect the clinical images of typhoid fever. It can be concluded that the individual characteristics and nutritional status variables have a direct effect on the clinical images.

Table 9. Indirect Effect Significance Test

Variable	*Total Effect*		t_{count}	*p-value*
	Estimate	*Standard deviation*		
Individual Characteristics ($\boldsymbol{\xi_1}$)	0.489	0.109	4.475	0.000*
Maternal Knowledge($\boldsymbol{\xi_2}$)	0.346	0.109	3.166	0.002*
Hygiene ($\boldsymbol{\xi_3}$)	0.182	0.077	2.366	0.02*

Based on Table 9, it can be seen that the individual characteristics variables, maternal knowledge and hygiene, have a $t_{count} > t_{tabel}$ (2.021) and a *p-value* < α (0.05), so H_0 is rejected. It can be concluded that the individual characteristics variables, maternal knowledge, and hygiene have an indirect effect on the clinical images. Based on the results of the significance test of direct and indirect effects between variables and after the indicators of understanding of care (X_{32}) and indigestion (Y_{52}) are excluded from the model, the following structural model equation is obtained structural model equation as follows.

1. Effect of Exogenous Variables on Nutritional Status.

$$\eta_1 = 0.489\xi_1 + 0.346\xi_2 + 0.182\xi_3 + \zeta_1$$

The model can be interpreted as follows:

a. Nutritional status is influenced by individual characteristics with an effect of 0.489. This means that if individual characteristics increase by one unit, then nutritional status will increase by 0.489 units.

b. Nutritional status is influenced by maternal knowledge with an effect of 0.346. This means that if maternal knowledge increases by one unit, then nutritional status will increase by 0.346 units.

c. Nutritional status is influenced by hygiene with an effect of 0.182. This means that if hygiene increases by one unit, then nutritional status will increase by 0.182 units.

2. Influence of Exogenous Variables and Nutritional Status on Clinical Features.

$$\eta_2 = 0.475\eta_1 + 0.674\xi_1 + 0.346\xi_2 + 0.182\xi_3 + \zeta_2$$

The model can be interpreted as follows:

a. The clinical images are influenced by nutritional status with an effect of 0.475. This means that if the nutritional status increases by one unit, the clinical images will increase by 0.475 units.

b. The clinical images are influenced by individual characteristics with an effect of 0.674. This means that if individual characteristics increase by one unit, the clinical images will increase by 0.674 units.

c. The clinical images are influenced by maternal knowledge indirectly through nutritional status, with an effect of 0.346.

d. The clinical images are influenced by hygiene indirectly through nutritional status, with an effect of 0.182.

Based on the results of the evaluation of the measurement model and hypothesis testing, a final path diagram was obtained, which can be seen in **Figure 4**.

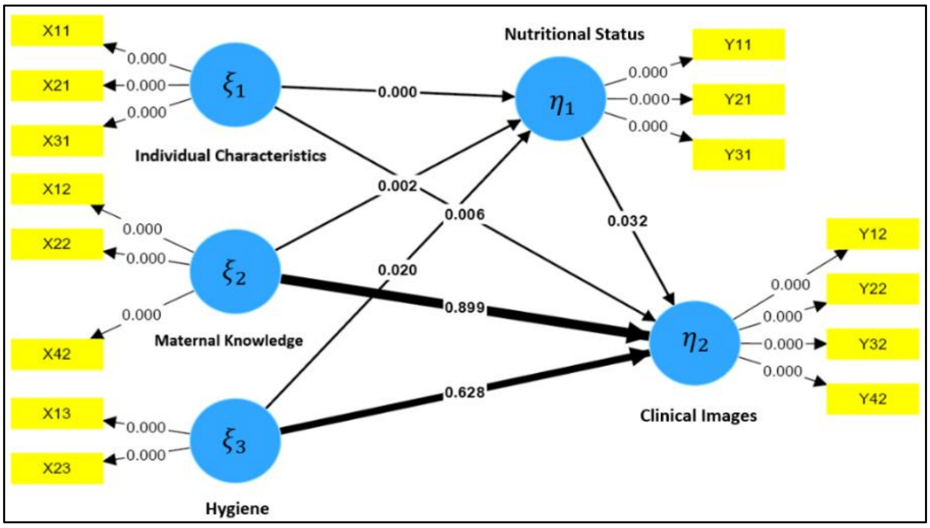

Figure 4. Final Construction Path Diagram

3.5 Structural Model (*Inner Model*) Evaluation

The R^2 value obtained is shown in **Table 10**.

Table 10. Measurement Model Significance Test Value

Endogenous Variable	R^2
Nutritional Status (η_1)	0.757
Clinical Images (η_2)	0.773

Based on **Table 10**, the R^2 value of nutritional status is 0.757, this value indicates that the contribution of individual characteristics, maternal knowledge, and hygiene variables to nutritional status is substantial or important, and it can also be said that variations in nutritional status can be explained by individual characteristics, maternal knowledge and hygiene by 75.7%. In addition, the R^2 value of the clinical images is 0.773, which indicates that the contribution of other variables to the clinical images is substantial, and it can be said that the variation in the clinical images can be explained by the variables of individual characteristics, maternal knowledge, hygiene, and nutritional status by 77.3%. Based on the R^2 value that has been obtained in **Table 10**, the *Q-square* value can be calculated as follows.

$$Q^2 = 1 - (1 - 0.757^2)(1 - 0.773^2) \tag{6}$$
$$Q^2 = 0.828$$

The Q^2 value of 0.828 was obtained, meaning that individual characteristics, maternal knowledge, hygiene, and nutritional status influenced the clinical images by 82.8%, and the other 17.2% was influenced by other factors outside the study.

4. CONCLUSIONS

The results of PLS-PM analysis show that individual characteristics and nutritional status have a direct effect on the clinical images. In addition, it was found that nutritional status is effective in mediating between individual characteristics, maternal knowledge, and hygiene on the clinical images, which can be proven by the indirect effect of individual characteristics, maternal knowledge, and hygiene through nutritional status on the clinical images. With a large influence of 82.8%.

Research on the clinical images of typhoid fever incidence can continue to be developed to produce better model accuracy, namely by adding indicators and other latent variables that are thought to be related to the clinical images of typhoid fever incidence. Future research can also choose hospitals or other related agencies as research locations, and obtain more diverse data or variables about typhoid fever patients from related agencies. It is intended that the results of the study can provide more significant benefits as a consideration for related agencies.

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