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THE BAYESIAN SEM APPROACH ON RELIGIOUS TOURISM AND SME'S ENTREPRENEURIAL OPPORTUNITY INTERRELATION IN RURAL AREA

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Abstract. *Economics, social, and culture are interrelated fields in developing a country. The social and cultural conditions that grow in an area affect how the economy develops in that area and its surroundings. This study analyzed a causal relationship between 60 nascent entrepreneurs in the rural area of religious tourism with Bayesian SEM to handle a small amount of data. Based on the results of the analysis, it was found that entrepreneurial motivation and cultural motivation had a significant effect on rural religious tourism. The latent variable of rural religious tourism and entrepreneurial motivation have a significant effect on SME's entrepreneurial opportunity. The entrepreneurial motivation variable has a correlation with the cultural motivation variable. This characteristic has established the rural Minangkabau heritage described on its strong religious tourism aspect as an SME's entrepreneurial challenge of nascent entrepreneurs.*

Keywords: *SEM, Bayesian, Small Sample Size, Entrepreneurial, Religious Tourism.*

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1. INTRODUCTION

The economic sector is important in the development of a country. Economic development cannot be separated from the role of entrepreneurship. Economics is inextricably linked to a region's culture [1]–[2]. T he culture that develops in an area affects how the economy develops, including the entrepreneurial culture, especially in Small and Medium Enterprises (SME). SME are the backbone of a country's economy. Because they have a small scale, small and medium enterprises are able to survive in the midst of global market instability [3].

ndonesia is known as a religious country. This aspect of religion affects various fields, including economic, social, and cultural ones. The study of interrelated entrepreneurial motivation, cultural motivation, rural religious tourism, and SME's entrepreneurial opportunity has important aspects to be explored for nascent entrepreneurs of rural areas.

The causal relationship between two or more variables can be analyzed through regression analysis. Regression analysis as part of statistics is widely used as a decision-making tool in various fields of exact sciences. For example, in the fields of medicine, education, and physics [4]–[7]. Not only in the exact field, but the application of regression analysis is also often used in the field of non-exact science, for example, in the social, cultural, and economic fields [8]–[11]. Regression analysis is a technique used to determine the causal relationship between independent and dependent variables [12]. There are two types of variables in a causal relationship. Namely, indicator variables that can be measured directly from the object or respondent and the variables that cannot be measured directly but are measured from two or more indicator variables called latent variables [13].

The variables in this study are variables that cannot be measured directly (latent variables). One of the statistical modeling techniques that is able to analyze the effect of latent variables with other latent variables is structural equation modeling (SEM). The SEM model has the ability to explain the relationship between indicator variables and latent variables as well as latent variables with other latent variables simultaneously. Modeling between these two types of variables certainly has relationships and problems that are not simple, and SEM can solve these complex problems [14]–[15]. SEM will produce a valid equation if the required assumptions are met, including normal multivariate and linearity with a large sample size (more than 200 samples) [13].

The need for data with a large sample size will undoubtedly be a problem, especially for research for which it is difficult to find data that matches its characteristics. In addition, a large sample size also requires a large amount of time, effort, and cost. An alternative method to solve the problem of a small sample size is through the Bayesian approach.

The SEM method with the Bayesian approach has recently received attention, where the Bayesian approach can overcome the problem of small sample sizes. This method can also overcome problems in modeling that do not meet the classical assumptions, such as normally distributed error, homogeneous error, uncorrelated error, and no multicollinearity problem [16]. In the Bayesian method, the model parameters to be estimated are assumed to be random variables that have a distribution. Information related to the model parameters is expressed as a prior distribution. This method combines information from the data (likelihood function) and information related to model parameters (prior distribution), eventually forming a posterior distribution.

2. RESEARCH METHODS

2.1 Research Data

This study uses primary data obtained from the survey of entrepreneurial motivation for nascent entrepreneurs at Batang Barus tourism-conscious business group, from Solok regency in the West Sumatra province of Indonesia. The survey involving 60 respondents was carried out in 2021 as nascent entrepreneurs of creative economy and tourism from the most of Minangkabau ethnic.

2.2 Research Variable and Hypothesis

This research data is assumed from several latent variables and indicators that will be used to the SEM model as shown in Table 1. Each indicator variable in the data uses a Likert scale of 1 to 5.

Table 1. Research Variable

Latent Variables		Indicator Variables
EXOGEN	**Entrepreneurial Motivation (X1)**	Entrepreneur (X11)
		Work (X12)
		Social (X13)
		Individual (X14)
		Economy (X15)
	Cultural Motivation (X2)	Public Identity (X21)
		Local Culture (X22)
		Religious Culture (X23)
		Festival (X24)
		Sustainability (X25)
ENDOGEN	**Rural Religious Tourism (Y1)**	Religious Access Receptivity (Y11)
		Modern Religious Tourism (Y12)
		Religious Advantages (Y13)
		Cultural Advantages (Y14)
		Economic Advantages (Y15)
	SME's Entrepreneurial Opportunity (Y2)	Socio-Economic Capacity Building (Y21)
		Business Idea Inspiration (Y22)
		Business Community (Y23)
		Supporting Institution (Y24)
		Business Association (Y25)
		Experience and Training (Y26)
		Business Development (Y27)

In this study, there are four latent variables, consisting of two exogenous latent variables, namely entrepreneurial motivation and cultural motivation, and two endogenous latent variables, namely rural religious tourism and SME's entrepreneurial opportunity. As presented in Table 1, each of these latent variables is measured by several indicator variables. The hypothetical model of the path diagram of latent variables and their indicators is illustrated in Figure 3.

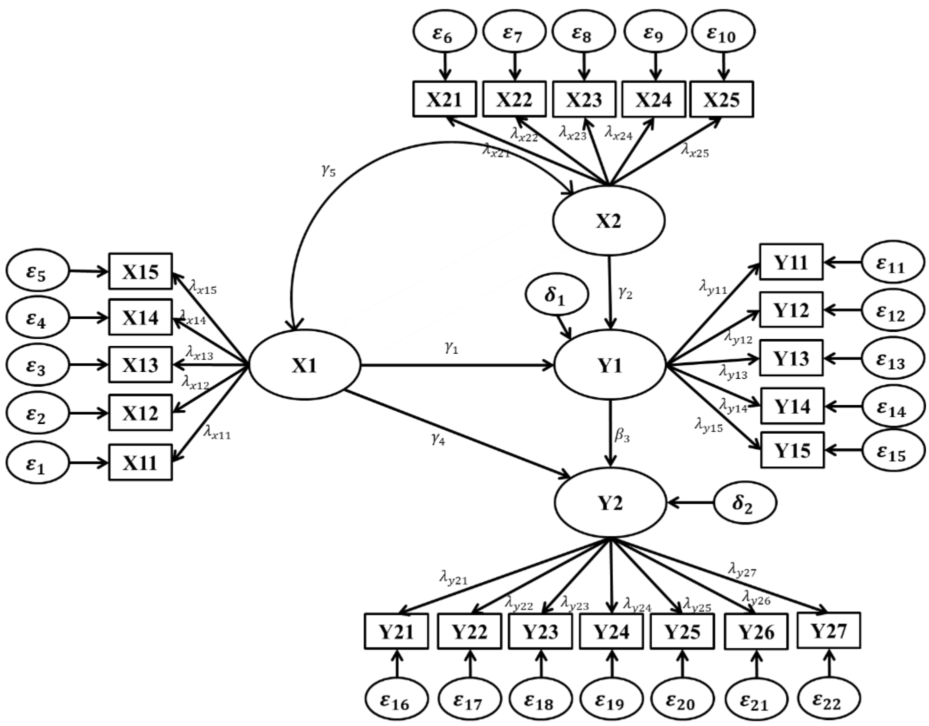

Figure 1. Hypothetical Model

In Figure 1, the hypothetical model used is that the latent variable Rural Religious Tourism (Y1) is affected by the latent variable Entrepreneurial Motivation (X1) and Cultural Motivation (X2). The latent variable of SME's Entrepreneurial Opportunity (Y2) is affected by the latent variable of Rural Religious Tourism (Y1) and Entrepreneurial Motivation (X1). Furthermore, there is a correlation between Entrepreneurial Motivation (X1) and Cultural Motivation (X2).

2.3 Data Analysis Method

Data analysis is the process of simplifying data into a form that is easier to read and implement. The data analysis tool for the model developed in this study uses Bayesian SEM, which is operated through a specific program. The following are the steps of Bayesian SEM analysis:Conduct theoretical studies related to modeling in Bayesian SEM

1) Conduct theoretical studies related to modeling in Bayesian SEM.
2) Structural Equation Modeling Analysis with Bayesian method.
   - Selection of prior distribution and likelihood function.
   - Bayesian SEM posterior computation.
   - MCMC method with Gibbs Sampling to obtain estimation results from the parameters of the posterior distribution model.
   - Test the significance of the model parameters by using a credible interval
   - Test the convergence of each model parameter.
3) Conclusion.

2.4 Structural Equation Modeling (SEM)

Sewal Wright developed the concept of SEM in 1934. Initially, this technique was known as path analysis and later narrowed down to SEM analysis [18]. SEM is a statistical technique that considers indicator variables and variables simultaneously. The data analysis technique using SEM was carried out to thoroughly explain the relationship between the variables in the study. SEM can be used to design a theory, but it is more intended to check and correct a model [19].

The measurement model is part of the SEM model that describes the relationship between latent variables and their indicator variables. Each latent variable is usually associated with multiple measures [18]. The relationship between latent variables and their measurement is done through the factor analytic measurement model, where each latent variable is modeled as a general factor for its measurement. The general form of the measurement model is as follows:

$$X = \Lambda_x \xi + \varepsilon \quad (1)$$

$$Y = \Lambda_y \eta + \varepsilon \quad (2)$$

where:

X : indicator variable vector for exogenous latent variable
Λ_x : loading factor matrix that connected exogenous latent variables and their indicators
ξ : vector of exogenous latent variable
ε : error vector of latent variable measurement with distribution $\varepsilon \sim N(0, \psi_\varepsilon)$
Y : vector of indicator variables for endogenous latent variables
Λ_y : loading factor matrix that connected endogenous latent variables and their indicators
η : vector of endogenous latent variable

The structural model includes the relationship between latent variables, and the relationship is considered to be linear. In the structural model, the regression relationship between endogenous latent variables (γ), regression of exogenous latent variables to endogenous latent variables (β) and regression between exogenous latent variables (Φ) can be analyzed. The structural equation model can be written into Eq. (3) [18],

$$\eta = B\eta + \Gamma\xi + \delta \quad (3)$$

where:

B : coefficient matrix that connected the endogenous latent variables

η : random vector of endogenous latent variables

Γ : correlation coefficient matrix of endogenous and exogenous latent variables in the structural model

ξ : exogenous latent variable vector.

δ : random vector for structural error with distribution $N(0, \psi_\delta)$

2.5 Bayesian Method

The Bayesian method is a parameter estimation method based on the Bayes theorem. The Bayesian method is a parameter estimation method where the parameter is a random variable that has a certain distribution.

Definition 1. The joint probability density function of n random variables $X_1, X_2, \ldots, X_n$ which is given the value $x_1, x_2, \ldots, x_n$ is denoted by $f(x_1, x_2, \ldots, x_n|\theta)$ which is a likelihood function. For certain values of $x_1, x_2, \ldots, x_n$, the likelihood function is a function of the parameter θ. If $X_1, X_2, \ldots, X_n$ are independent random samples then:

$$L(x_i|\theta) = f(x_1|\theta)f(x_2|\theta) \ldots f(x_n|\theta)$$
$$L(x_i|\theta) = \prod_{i=1}^{n} f(x_i|\theta)$$

where θ is the unknown parameter.

The prior distribution is the initial distribution that provides information about the parameters. First, we have to determine the prior distribution of the parameters to get the posterior distribution. The accuracy of determining the prior distribution greatly affects the accuracy of the posterior distribution obtained. The posterior distribution is a conditional density function θ if the observed value *x* is known, it can be written as follows [20]:

$$f(\theta|x) = \frac{f(\theta,x)}{f(x)} \quad (4)$$

If θ is continuous, the prior and posterior distributions of θ can be represented by the density function. The conditional density function of one random variable, if the value of the second random variable is known, is only the joint density function of the two random variables divided by the marginal density function of the second random variable, but the joint density function $f(\theta, x)$ and the marginal density function $f(x)$ are generally not known, and only the prior distribution and the likelihood function are usually expressed. The joint density function can be written in the form of the prior distribution and the likelihood function as follows

$$f(\theta, x) = f(x|\theta)f(\theta) \quad (5)$$

where $f(x|\theta)$ is the likelihood function and $f(\theta)$ is the density function of the prior distribution. Then the marginal density function for a continuous distribution can be expressed as

$$f(x) = \int_{-\infty}^{\infty} f(\theta, x)\, d\theta = \int_{-\infty}^{\infty} f(x|\theta)f(\theta)\, d\theta \quad (6)$$

So from Eq. (5), (6) and (7), the posterior density function for continuous random variables can be written as

$$f(x|\theta) \propto f(x|\theta)f(\theta) \quad (7)$$

The mean and variance of the posterior distribution were used to determine the Bayesian estimate of the unknown θ parameter.

2.6 Markov Chain Monte Carlo (MCMC)

The Markov Chain Monte Carlo (MCMC) method estimates model parameters using numerical simulation techniques used to solve complex modeling problems. In the Bayesian method, the parameter estimation obtained uses the posterior marginal distribution. The solution process to determine the posterior marginal distribution is complex and complicated because it requires a high level of integration. A numerical simulation technique is used to obtain the posterior marginal distribution, namely MCMC.

Markov Chain is an iterative process of a set of independent variables such that $f\left(\theta^{i+1}\middle|\theta^i, \dots, \theta^1\right) = f(\theta^{i+1}|\theta^i)$, which means the process to estimate the parameter at the time of the iteration $(i+1)$ is only affected by the value at the time of the i-th iteration [21].

2.7 Structural Equation Modeling with Bayesian Method

Bayesian SEM has several advantages over other classical methods such as Maximum Likelihood Estimation (MLE), generalized, and weighted least squares. Some of the advantages of the Bayesian SEM method are that it can include the prior information about parameters, treat unidentified models more effectively, the assumptions used to form the size of the latent variable can be treated stochastically, and the modeling process does not depend on large data that is normally distributed [16].

In SEM with maximum likelihood approach, is not considered as a random variable where θ is $\Phi, \Psi, \Lambda, \Gamma$. Whereas in Bayesian SEM, θ is considered as a random variable that has a distribution. Furthermore, the distribution is referred to as the prior distribution. If M is an SEM equation with an unknown parameter θ then the probability density function of θ is $p(\theta|M)$. If Bayesian inference is based on observational data Y, then the joint distribution of Y and θ on M is

$$p(Y,\theta|M) = p(Y|\theta,M)p(\theta) = p(\theta|Y,M)p(Y|M) \tag{8}$$

it is known that $p(Y|M)$ does not depend on θ and by assuming Y has been determined and constant then we can get

$$\log\, p(\theta|Y,M) \propto \log p(Y|\theta,M) + \log\, p(\theta) \tag{9}$$

where:
M : any form of SEM with unknown θ parameter vector
Y : observational data with size n
$p(\theta|M)$: prior distribution of in θ the M model
$p(Y,\theta|M)$: joint probability distribution of Y and θ provided that the M model is known
$p(\theta|Y,M)$: probability distribution of the posterior
$p(Y|\theta,M)$: likelihood function

The factor analysis model related to the measurement equation is formulated as follows

$$y_i = \Lambda\omega_i + \varepsilon_i, \qquad i = 1, \dots, n \tag{10}$$

where y_i is a random vector of observations, the loading factor matrix Λ sized $\mathrm{p} \times \mathrm{q}$, while ω_i is partitioned into $(\mathrm{q}_1 \times 1)$ which is a vector of exogenous latent variables and $(\mathrm{q}_2 \times 1)$ is a vector of endogenous latent variables and an error vector for measurement errors ε_i sized $\mathrm{p} \times 1$, which is assumed to be $\mathrm{N}(0, \Psi_\varepsilon)$ distributed where Ψ_ε is a diagonal matrix with elements $\psi_{\varepsilon k}$. The models for structural equations are as follows:

$$\eta_i = \Gamma\omega_i + \delta_i \tag{11}$$

Where Γ is a loading coefficient matrix of size $\mathrm{q}_1 \times \mathrm{q}_2$, δ_i is a random error vector of size $\mathrm{q}_2 \times 1$, and δ_i is $\mathrm{N}(0, \Psi_\delta)$ distributed where Ψ_δ is a diagonal matrix with $\psi_{\delta k}$ elements.

The main thing that distinguishes Bayesian estimation from others is the prior distribution. The prior distribution is the initial distribution that must be determined before determining the posterior distribution [16]. Determination of the prior distribution plays an important and significant role in Bayesian analysis. The prior distribution used in the Bayesian approach in general for statistical problems is the conjugate prior distribution.

In Bayesian SEM, the parameter values of ={Λ,Ψ_ε,Φ,Ψ_δ,Γ} will be estimated. The prior used is the conjugate prior. The prior for the parameters to be estimated is as follows:

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

$$(\Lambda_k|\psi_{\varepsilon k}) \sim N(\Lambda_{0k}, \psi_{\varepsilon k} H_{0yk})$$

$$\Phi^{-1} \sim \mathrm{W}_q(\mathrm{R}_0, \rho_0)$$

where $Gamma(\alpha,\beta)$ is Gamma distribution with forming parameter $\alpha > 0$ and inverse parameter $\beta > 0$, $\mathrm{W}_q(\mathrm{R}_0, \rho_0)$ shows Wishart distribution with dimension q and $\alpha_{0\varepsilon k}, \beta_{0\varepsilon k}, \Lambda_{0k}, H_{0yk}, \mathrm{R}_0, \rho_0$ is assumed hyperparameter can be assigned a value from prior information in previous studies or other sources.

2.8 MCMC with Gibbs Sampling

The estimation process using the MCMC method is carried out by taking random samples repeatedly through the fully conditional posterior distribution. In this way, we know the characteristics for each parameter in a complex composite posterior distribution without having to calculate or know how the marginal function of that parameter is. In this research, the chosen MCMC method is Gibbs Sampling. The stages of Gibbs Sampling in generating the posterior distribution are as follows:

1) Takes an initialization $\Omega^{(j)}, \Psi_\varepsilon^{(j)}, \Lambda^{(j)}, \Phi^{(j)}$
2) Generate the value of $\Omega^{(j+1)}$ from $p(\Omega|\Psi_\varepsilon^{(j)}, \Lambda^{(j)}, \Phi^{(j)}, Y)$
3) Generate the value of $\Psi_\varepsilon^{(j+1)}$ from $p(\Psi_\varepsilon|\Omega^{(j+1)}, \Lambda^{(j)}, \Phi^{(j)}, Y)$
4) Generate the value of $\Lambda^{(j+1)}$ from $p(\Lambda|\Omega^{(j+1)}, \Psi_\varepsilon^{(j+1)}, \Phi^{(j)}, Y)$
5) Generate the value of $\Phi^{(j+1)}$ where j is the number of iterations with M iterations or $j = 1, \ldots, M$.

Bayesian estimation for parameter vector θ is obtained from

$$\hat{\theta} = \frac{1}{M}\sum_{j=1}^{M} \theta^j \quad (12)$$

$$\widehat{var}(\theta|Y) = \frac{1}{M-1}\sum_{j=1}^{M}(\theta^j - \hat{\theta})(\theta^j - \hat{\theta})^T \quad (13)$$

For latent variable vectors, Bayesian estimates can be obtained from

$$\widehat{\omega_i} = \frac{1}{M}\sum_{j=1}^{M} \omega_i^j \quad (14)$$

$$\widehat{var}(\omega_i|Y) = \frac{1}{M-1}\sum_{j=1}^{M}(\omega_i^j - \widehat{\omega_i})(\omega_i^j - \widehat{\omega_i})^T \quad (15)$$

In this study, the application of MCMC with Gibbs Sampling was carried out to obtain the estimation results of the posterior distribution on each unknown parameter, including the latent variable. To obtain the characteristics of the posterior distribution, sufficient observations are needed. For this reason, a number of observations are generated in such a way that the resulting empirical distribution is close to the actual distribution.

3. RESULTS AND DISCUSSION

3.1. Parameter Estimation

The structure of the path relationship between latent variables is illustrated in Figure 1. The hypotheses for the structural equation model in this study are

$$Y1 = \gamma_1 X1 + \gamma_2 X2 + \delta_1$$

$$Y2 = \beta_3 Y1 + \gamma_4 X1 + \delta_2$$

The measurement equation model for the latent variables are

1) The measurement equation model of Entrepreneurial Motivation

$$X_{1r} = \lambda_{x1r} X_1 + \varepsilon, \qquad r = 1, \ldots, 5$$

2) The measurement equation model of Cultural Motivation

$$X_{2s} = \lambda_{x2s} X_2 + \varepsilon, \qquad s = 1, \ldots, 5$$

3) The measurement equation model of Rural Religious Tourism

$$Y_{1t} = \lambda_{y1t} Y_1 + \varepsilon, \qquad t = 1, \ldots, 5$$

4) The measurement equation model of SME's Entrepreneurial Opportunity

$$Y_{2u} = \lambda_{y2u} Y_2 + \varepsilon, \qquad u = 1, \dots, 7$$

Furthermore, by using the data obtained from the data from nascent entrepreneurs of creative economy and tourism survey of 60 respondents, a model will be made using the hypothesis model above. The model parameter estimation process has reached convergence after 90000 iterations. The parameter estimation results can be seen in Table 2.

Table 2. Parameter Estimation Results

Parameter	Mean	MC Error	Standard Deviation	50% LB	50% UB	Significance
γ_1	0.195	0.021	0.493	0.072	0.498	Significant
γ_2	1.286	0.022	0.468	0.960	1.548	Significant
β_3	0.320	0.009	0.330	0.110	0.518	Significant
γ_4	1.121	0.025	0.728	0.637	1.536	Significant
γ_5	0.113	0.002	0.045	0.080	0.138	Significant
λ_{x11}	1.000	-	-	-	-	Significant
λ_{x12}	1.764	0.017	0.440	1.460	1.997	Significant
λ_{x13}	2.109	0.018	0.521	1.744	2.387	Significant
λ_{x14}	2.140	0.027	0.574	1.745	2.435	Significant
λ_{x15}	1.645	0.017	0.404	1.364	1.858	Significant
λ_{x21}	1.000	-	-	-	-	Significant
λ_{x22}	1.434	0.023	0.412	1.141	1.654	Significant
λ_{x23}	1.682	0.027	0.499	1.341	1.932	Significant
λ_{x24}	0.948	0.016	0.326	0.720	1.126	Significant
λ_{x25}	1.388	0.022	0.380	1.115	1.595	Significant
λ_{y11}	1.000	-	-	-	-	Significant
λ_{y12}	1.115	0.008	0.207	0.976	1.227	Significant
λ_{y13}	0.996	0.008	0.239	0.832	1.135	Significant
λ_{y14}	1.030	0.007	0.208	0.889	1.147	Significant
λ_{y15}	1.042	0.009	0.274	0.860	1.196	Significant
λ_{y21}	1.000	-	-	-	-	Significant
λ_{y22}	1.137	0.01	0.244	0.974	1.262	Significant
λ_{y23}	0.727	0.006	0.174	0.613	0.817	Significant
λ_{y24}	0.904	0.009	0.207	0.763	1.013	Significant
λ_{y25}	1.563	0.011	0.276	1.377	1.689	Significant
λ_{y26}	0.789	0.007	0.204	0.652	0.905	Significant
λ_{y27}	1.074	0.009	0.210	0.932	1.178	Significant
δ_1	0.076	0.002	0.049	0.041	0.103	Significant
δ_2	0.471	0.006	0.171	0.350	0.568	Significant
ε_1	0.143	0.001	0.033	0.119	0.162	Significant
ε_2	0.356	0.002	0.083	0.297	0.404	Significant
ε_3	0.433	0.002	0.103	0.361	0.490	Significant
ε_4	0.466	0.003	0.112	0.386	0.533	Significant
ε_5	0.213	0.002	0.054	0.175	0.244	Significant
ε_6	0.406	0.002	0.086	0.344	0.454	Significant
ε_7	0.285	0.002	0.066	0.238	0.325	Significant
ε_8	0.469	0.004	0.104	0.394	0.531	Significant
ε_9	0.361	0.002	0.075	0.308	0.403	Significant
ε_{10}	0.173	0.001	0.047	0.140	0.201	Significant
ε_{11}	0.316	0.002	0.075	0.263	0.360	Significant
ε_{12}	0.257	0.002	0.067	0.210	0.295	Significant
ε_{13}	0.636	0.004	0.139	0.539	0.714	Significant
ε_{14}	0.355	0.002	0.083	0.296	0.404	Significant
ε_{15}	0.866	0.005	0.183	0.735	0.970	Significant
ε_{16}	0.683	0.003	0.147	0.579	0.769	Significant
ε_{17}	0.846	0.004	0.174	0.722	0.951	Significant
ε_{18}	0.522	0.003	0.108	0.445	0.583	Significant
ε_{19}	0.650	0.004	0.142	0.550	0.728	Significant
ε_{20}	0.168	0.002	0.086	0.107	0.219	Significant
ε_{21}	0.812	0.005	0.169	0.693	0.908	Significant
ε_{22}	0.413	0.003	0.094	0.347	0.466	Significant

From Table 2, it can be seen that all parameter has a small MC Error value (close to zero) and has a confidence interval that does not contain zero so that all parameters are significant. Thus it can be concluded that:

- Entrepreneurial Motivation (X1) and Cultural Motivation (X2) variables have a significant effect on Rural Religious Tourism (Y1). The latent variable Rural Religious Tourism (Y1) and Entrepreneurial Motivation (X1) have a significant effect on SME's Entrepreneurial Opportunity (Y2). The entrepreneurial Motivation variable (X1) has a correlation with the Cultural Motivation variable (X2).
- Entrepreneurial Motivation (X1) and Cultural Motivation (X2) variables have a positive path coefficient value so that they are proportional to the Rural Religious Tourism variable (Y1). Likewise, the latent variable Rural Religious Tourism (Y1) and Entrepreneurial Motivation (X1) is proportional to the SME's Entrepreneurial Opportunity (Y2) variable because it has a positive path coefficient value.

3.2. Parameters Convergence Test

The next step in the SEM method with the Bayesian approach is to test the convergence of the model parameters whose values have been estimated. The test was carried out using a history trace plot, density plot and Standar Error. Figure 2 presents the trace plot parameters of the model.

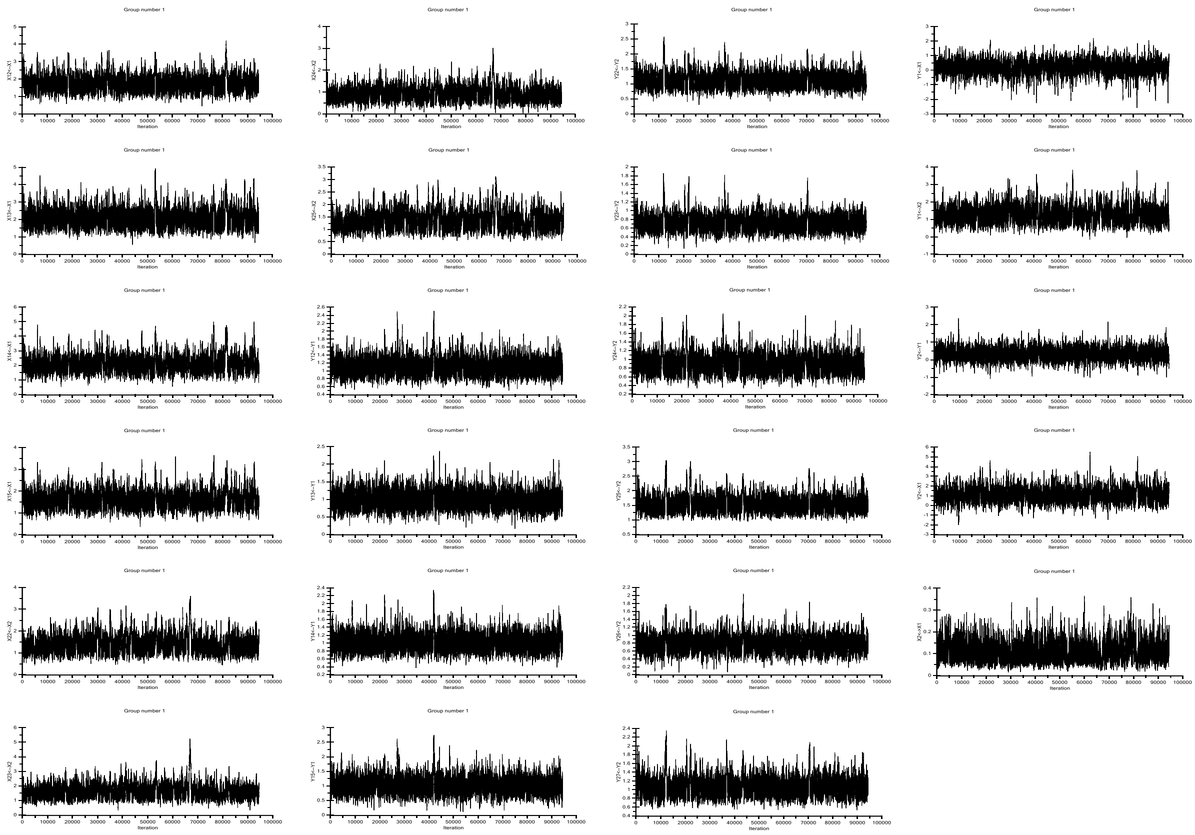

Figure 2. History Trace Plot

Based on Figure 2, it can be concluded that the convergence assumption is fulfilled. The data distribution has been stable because it lies between two parallel horizontal lines. Figure 3 below presents the density plot of the parameters in the model.

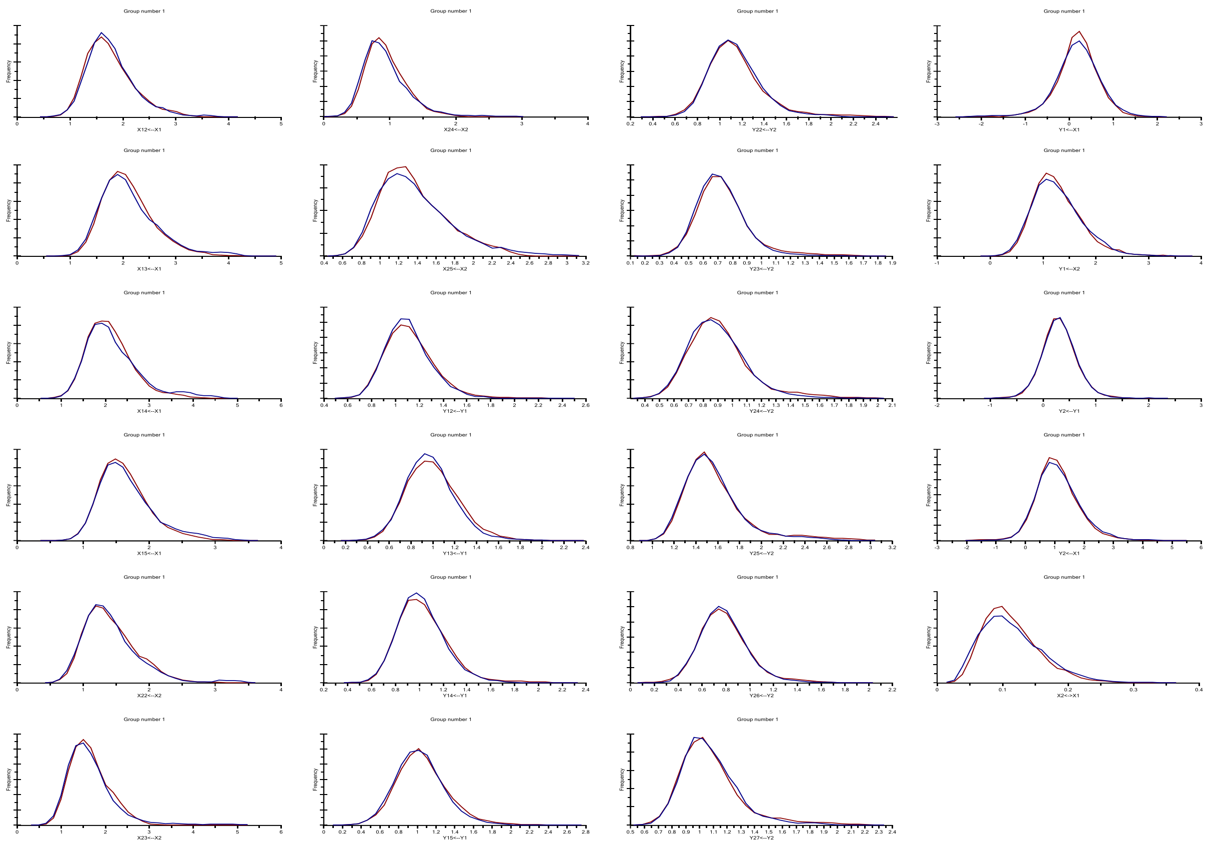

Figure 3. Density Plot

In Figure 3, the density plot shows a normally distributed curve. Thus the model has converged. The way to test the convergence of the other model parameters is to compare the MC Error value and the 5% of the standard deviation of each model parameter. Table 3 presents the MC Error of the model parameters.

Table 3. MC Error

Parameter	Mean	MC Error	Standard Deviation	50% LB	50% UB	5% SD	Convergence
γ_1	0.195	0.021	0.493	0.072	0.498	0.025	Convergent
γ_2	1.286	0.022	0.468	0.960	1.548	0.023	Convergent
β_3	0.320	0.009	0.330	0.110	0.518	0.017	Convergent
γ_4	1.121	0.025	0.728	0.637	1.536	0.036	Convergent
γ_5	0.113	0.002	0.045	0.080	0.138	0.002	Convergent
λ_{x12}	1.764	0.017	0.440	1.460	1.997	0.022	Convergent
λ_{x13}	2.109	0.018	0.521	1.744	2.387	0.026	Convergent
λ_{x14}	2.140	0.027	0.574	1.745	2.435	0.029	Convergent
λ_{x15}	1.645	0.017	0.404	1.364	1.858	0.020	Convergent
λ_{x22}	1.434	0.023	0.412	1.141	1.654	0.021	Convergent
λ_{x23}	1.682	0.027	0.499	1.341	1.932	0.025	Convergent
λ_{x24}	0.948	0.016	0.326	0.720	1.126	0.016	Convergent
λ_{x25}	1.388	0.022	0.380	1.115	1.595	0.019	Convergent
λ_{y12}	1.115	0.008	0.207	0.976	1.227	0.010	Convergent
λ_{y13}	0.996	0.008	0.239	0.832	1.135	0.012	Convergent
λ_{y14}	1.030	0.007	0.208	0.889	1.147	0.010	Convergent
λ_{y15}	1.042	0.009	0.274	0.860	1.196	0.014	Convergent
λ_{y22}	1.137	0.01	0.244	0.974	1.262	0.012	Convergent
λ_{y23}	0.727	0.006	0.174	0.613	0.817	0.009	Convergent

λ_{y24}	0.904	0.009	0.207	0.763	1.013	0.010	Convergent
λ_{y25}	1.563	0.011	0.276	1.377	1.689	0.014	Convergent
λ_{y26}	0.789	0.007	0.204	0.652	0.905	0.010	Convergent
λ_{y27}	1.074	0.009	0.210	0.932	1.178	0.011	Convergent

Based on Table 3, for each parameter, it can be seen that the MC Error value is less than 5% of the standard deviation. This means that for the convergence test with the MC Error, the model parameters have converged. Thus, based on the convergence examination, namely trace plot, density plot, and MC error, it can be concluded that the hypothetical model has met the convergence criteria, which means that the model can be accepted.

Thus, the measurement model equation is obtained as follows

$$X_{11} = 1.000\, X_1 + 0.143 \qquad Y_{12} = 1.115\, Y_1 + 0.257$$
$$X_{12} = 1.764\, X_1 + 0.356 \qquad Y_{13} = 0.996\, Y_1 + 0.636$$
$$X_{13} = 2.109\, X_1 + 0.433 \qquad Y_{14} = 1.030\, Y_1 + 0.355$$
$$X_{14} = 2.140\, X_1 + 0.466 \qquad Y_{15} = 1.042\, Y_1 + 0.866$$
$$X_{15} = 1.645\, X_1 + 0.213 \qquad Y_{21} = 1.000\, Y_2 + 0.683$$
$$X_{21} = 1.000\, X_2 + 0.406 \qquad Y_{22} = 1.137\, Y_2 + 0.846$$
$$X_{22} = 1.434\, X_2 + 0.285 \qquad Y_{23} = 0.727\, Y_2 + 0.522$$
$$X_{23} = 1.682\, X_2 + 0.469 \qquad Y_{24} = 0.904\, Y_2 + 0.650$$
$$X_{24} = 0.948\, X_2 + 0.361 \qquad Y_{25} = 1.563\, Y_2 + 0.168$$
$$X_{25} = 1.388\, X_2 + 0.173 \qquad Y_{26} = 0.789\, Y_2 + 0.812$$
$$Y_{11} = 1.000\, Y_1 + 0.316 \qquad Y_{27} = 1.074\, Y_2 + 0.413$$

The structural model equation is obtained as follows

$$Y1 = 0.195X1 + 1.286X2 + 0.076$$
$$Y2 = 0.320Y1 + 1.121X1 + 0.471$$

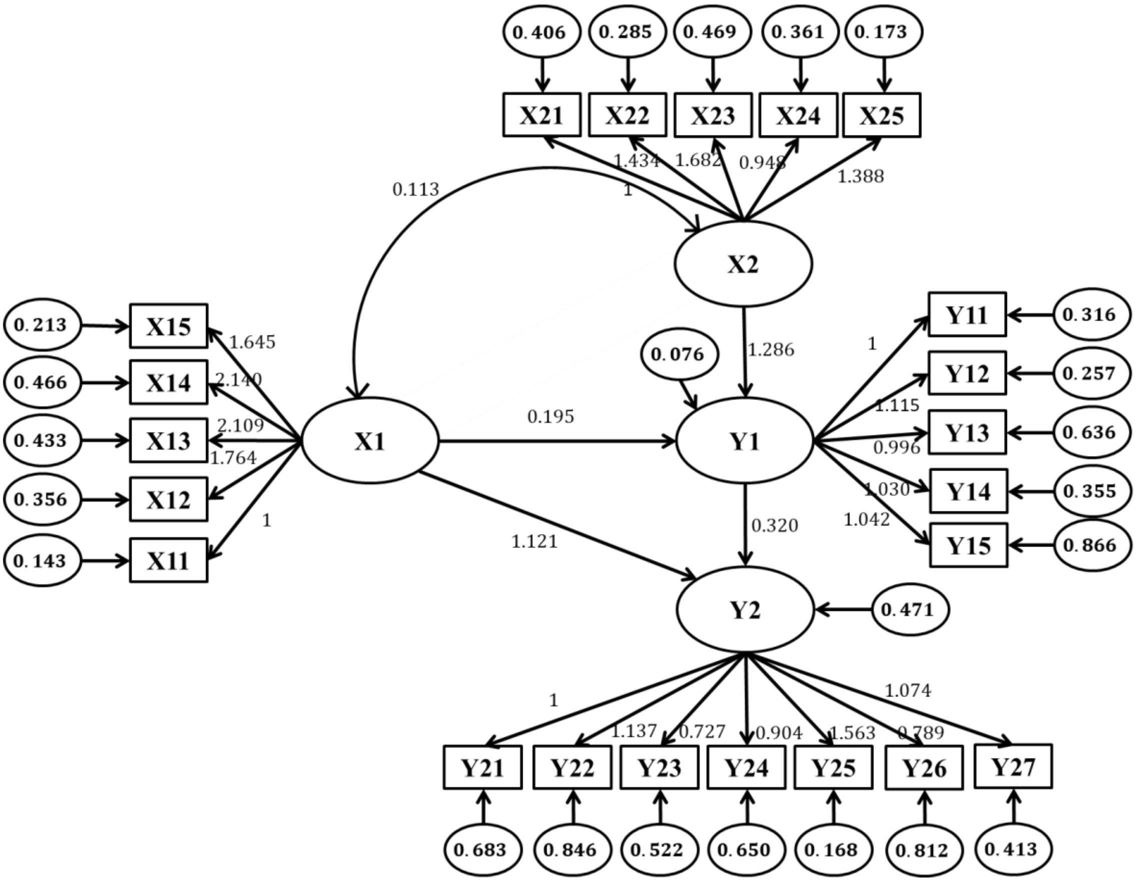

Figure 4. Bayesian SEM Model Result

The model can be formed into a path diagram, as shown in Figure 4. The measurement model shows all indicators are significantly influenced to measure each of the latent variables. The structural model performs at a significant level for all parameters. The entrepreneurial motivation and cultural motivation variables have a significant effect on the activity of rural religious tourism. The latent variable of rural religious tourism and entrepreneurial motivation have a significant effect on the activity of SME's entrepreneurial opportunity for nascent entrepreneurs. In addition, the entrepreneurial motivation has a correlation with the cultural motivation variable. This is very specific to the sample area of Minangkabau culture.

The path analysis of Figure 4 shows entrepreneurial motivation and cultural motivation have a positive path. This is to indicate that they are proportional to activity in rural religious tourism. The path analysis also shows that the latent variable of rural religious tourism and entrepreneurial motivation have a proportional effect on the SME's entrepreneurial opportunity. This characteristic of nascent entrepreneurs from the sample area has established the Minangkabau heritage as a merchant community since ancient times, where the Minangkabau people have given strong attention to the religious tourism aspect of SME's entrepreneurial to remote areas. The remote area of Minangkabau heritage is well known as the people with a strong unity of religion and trade, where the activities are developed by strong social and economic motivation.

4. CONCLUSIONS

Several conclusions can be drawn from the research that has been conducted, including the following:

1. The motivation of nascent entrepreneurs in the rural area of religious tourism with a small sample size (60 data points) can be modeled using the Structural Equation Modeling (SEM) parameter estimation method through the Bayesian approach. In the measurement model, all indicators are significant, so that all indicators are able to measure each of the latent variables.
2. In the structural model, all parameters are significant. Entrepreneurial Motivation (X1) and Cultural Motivation (X2) variables have a significant effect on Rural Religious Tourism (Y1). The latent

variables rural Religious Tourism (Y1) and Entrepreneurial Motivation (X1) have a significant effect on SME's Entrepreneurial Opportunity (Y2). The entrepreneurial Motivation variable (X1) has a correlation with the Cultural Motivation variable (X2).

3. Entrepreneurial Motivation Variables (X1) and Cultural Motivation (X2) have a positive path coefficient value so that they are proportional to the Rural Religious Tourism variable (Y1). Likewise, the latent variables Rural Religious Tourism (Y1) and Entrepreneurial Motivation (X1) are proportional to the SME's Entrepreneurial Opportunity (Y2) variable because it has a positive path coefficient value. This characteristic of nascent entrepreneurs has established the Minangkabau heritage, known as the merchant community, with strong attention to religious tourism aspects in SME's entrepreneurial activity in remote areas.

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