DOI: https://doi.org/10.34123/jurnalasks.v15i2.442

POLITEKNIK STATISTIKA STIS

Jurnal Aplikasi Statistika & Komputasi Statistik
Vol. 16 No. 1, June 2024
e- ISSN: 2615-1367, p-ISSN:2086-4132

Available online at https://jurnal.stis.ac.id/

Digital Literacy in Mediating the Influence of Education, Demography, and Employment on Poverty

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ARTICLE INFO

Article history:
Received 10 December, 2023
Revised 10 May, 2024
Accepted 7 May, 2024
Published 30 June, 2024

Keywords:
Digital Literacy, Education, Demography, Employment, Poverty, SEM-PLS

Abstract

Introduction/Main Objectives: This study investigated the influence of education, demography, and employment on poverty with digital literacy as a mediating variable. **Background Problems:** interrelationship has not been investigated before, either in Indonesia or in other countries, even though some studies have indicated the importance of providing digital literacy training to eradicate poverty in poor communities. **Novelty:** using the Structural Equation Modeling (SEM) Partial Least Square (PLS) method in analyzing data and modeling relationships between Education, demographic, and employment factors and poverty with digital literacy as a mediating variable that acts as a link. **Research Methods:** A structural Equation Modeling (SEM) with the Partial Least Square (PLS) method was applied. **Finding/Results:** Significant indicators found are four indicators of education and digital literacy variables, two indicators of demographic and employment variables, and three indicators of poverty variables. It was found that education and employment variables had a significant influence on poverty with a negative influence. We found that no variable has a significant effect on digital literacy and there is no significant effect of digital literacy on Poverty.

1. Introduction

Poverty according to the Badan Pusat Statistik (BPS) is a condition where a person has an income below the basic needs of the general public [1]. Efforts to reduce poverty are a United Nations program in 2015 Sustainable Development Goals (SDGs) as a global invitation are in line with efforts to protect the earth and ensure that by 2030, all humans can live in peace and prosperity. No Poverty is the first point in te SDGs which means the global community collaboratively agrees to eradicate poverty on earth. Poverty can be attributed to several other Global Goal factors such as the quality of education, demography, employment, and the use of digitalization [2].

According to Lawrence Cremin in Klimczuk, education is efforts made to convey or acquire knowledge, values, attitudes, and skills. Demography is the study of human populations and changes in their quantity related to migration, births, and deaths [3]. Employment is a social interaction between employers and workers, where workers provide certain services and receive predetermined and negotiable wages [4]. According to Schallmo and Williams [5], digitalization is the use of digital technology and data to generate revenue, improve business, change business processes, and create an ecosystem for digital business. Digital literacy is a skill needed to do something by utilizing communication and access to information using digital technology such as the Internet, social media, and mobile devices.

Previous research using SEM-PLS was conducted by Nurhafifah et al. [6], to see the relationship between economic, educational, and health factors to poverty in Indonesia in districts/cities that have a percentage of poor people above the percentage of poor people in Indonesia. The results of the study stated that the heterogeneity of poverty variables can be explained by economic, educational, and health variables. The increase of digitalization in all aspects of our lives made digital literacy one of the important life skills needed to have a better life. Advancing the study done by Nurhafifah et al., the authors were interested in using the Structural Equation Modeling (SEM) Partial Least Square (PLS) method in analyzing data and modeling relationships between Education, demographic, and employment factors and poverty with digital literacy as a mediating variable that acts as a link [6]. This interrelationship has not been investigated before, either in Indonesia or in other countries, even though some studies have indicated the importance of providing digital literacy training to eradicate poverty in poor communities [7].

SEM is a statistical approach to testing hypotheses about the relationship between observed variables (indicators) and latent variables [8]. PLS is an SEM method used to estimate path relationships between latent variables and between latent variables and their indicators in complex problems [9]. PLS data analysis techniques consist of parameter estimation and model evaluation, parameter estimation is the first step of SEM-PLS data analysis that will determine the next data analysis. Parameter estimation aims to produce values that relate between indicators and their latent variables and the relationship between latent variables. So for the next stage of analysis, which indicators can still be used or not will be evaluated.

2. Material & Methods

2.1. Partial Least Square- Structural Equation Modeling (PLS-SEM)

Structural Equation Modeling (SEM) is a multivariate statistical technique used to model complex relationships between directly observable variables (indicators) and non-directly observable variables (latent variables). SEM analysis techniques involve the solution of systems of linear equations, regression, factor analysis, path analysis, and growth curve modeling [10]. There are two variables in SEM analysis, namely variables that can be observed directly or commonly called indicators and variables that cannot be observed directly called latent variables. There are two types of latent variables, namely endogenous latent variables as response variables with notation η (eta) and exogenous latent variables as explanatory variables with notation ξ (xi).

There are two types of SEM, namely the covariant-based SEM (CB-SEM) and the variance-based SEM (SEM-PLS). CB-SEM is appropriate for theoretical tests and obtaining explanations based on test results with a series of complex analyses, CB-SEM also requires a relatively large number of samples for accurate results. While SEM-PLS aims to test the existence of relationships or predictive influences between variables, SEM-PLS can use samples that are not large. The data and objectives of this study that fit these criteria are using SEM-PLS [11].

Partial Least Square is an SEM data analysis technique to simulate the connection between response variables and other explanatory variables. A simple interpretation is given to show an easy-to-apply method of forming predictive equations. PLS-SEM consists of two models, including a measurement model and a structural model. The measurement model is a model of the relationship between latent variables and indicators, this model is analyzed to see the validity and reliability of each indicator used. The structural model is a model of relationships between latent variables, this model is to see the relationships in the model and test hypotheses on prediction models [12].

Indicators in SEM-PLS data analysis are built through two models, including the reflective model and the formative model. The reflective model describes indicators that are affected by latent variables, the formative model is an indicator model that affects latent variables. The structural models (inner models) are designed to model the relationship between latent variables, in the form of:

$$\eta_j = \sum \gamma_i \xi_i + \zeta, \tag{1}$$

where:
I = the index of exogenous latent variables
γ_i = the connecting pathway coefficient of the endogenous (η) with exogenous (ξ)
ζ = the measurement error rate.

Measurement models (outer models) describe the relationship between latent variables and their indicators. In this study, the authors used a reflective-type measurement model with the following conditions:

$$X = \lambda_X \xi + \delta_X, \tag{2}$$

$$Y = \lambda_Y \eta + \varepsilon_Y, \tag{3}$$

X is the indicator of exogenous latent variables (ξ). Y is the indicator of endogenous latent variables (η). ξ is the exogenous latent variable. η is the endogenous latent variable. λ_X and λ_Y are a loading matrix, associating latent variables with indicators. δ_X ε_Y is the measurement error rate.

That model specifications do not yet describe latent variable values therefore weight relations must be defined. One of the characteristics of SEM-PLS analysis is estimating the value of the latent variable score. Weights are described with the symbol w_{jk}, so the estimated latent variable score can be written as follows:

$$\xi_j = \sum_{k=1}^{K_j} w_{jk} X_{jk}. \tag{4}$$

The PLS algorithm is a link between simple and multiple regression using an estimation approach ordinary least square [13].

2.2. PLS Algorithm Stage 1

The first stage aims to generate weights to calculate the score of latent variables. In calculating weight, we used iteration techniques based on the built model, namely structural and measurement models. At this stage, it depends heavily on the relationship between the score of the latent variable in the structural model and the indicator linked to the score of the latent variable. The estimation of the parameters of the measurement model is formed through equation (4). While the estimation of structural model parameters is formed through the formula:

$$z_j \propto \sum_{i=1, i\neq j}^{J} e_{ji} \xi_i, \tag{5}$$

z_j is the symbol of the latent variable to be reestimated. Symbol ∝ means left-hand variables represent right-hand variables. The weight of the structural model e_{ji} can be estimated using a factoring scheme, this scheme takes into account the direction of the sign and the strength of the path on the structural model. The factor scheme is defined as follows [14]:

$$e_{ji} = \{cor(\xi_i, \xi_j)\ 0\ , related\ \xi_i\ and\ \xi_j\ \ others. \tag{6}$$

The next step at this stage is to update the measurement model after estimating the approximate value of the weight value. Updating the weights of the measurement model can use the reflective indicator model:

$$X_{jk} = \lambda_{jk} \xi_j + \delta_{jk}. \tag{7}$$

The renewal weight value for an exogenous latent variable is defined as follows:

$$w_{jk} = \left(z_j' z_j\right)^{-1} z_j' X_{jk}, \tag{8}$$

Next is the convergence check at the iteration stage, the convergence is checked by comparing the weights of the new values at each current step and the previous step with the following criteria:

$$\left|w_{jk}^{s} - w_{jk}^{s-1}\right| < 10^{-5}. \tag{9}$$

2.3. PLS Algorithm Stage 2

The second stage is to calculate the estimation of the path coefficient and loading factor in structural models and measurement models. Path coefficients in structural models are estimated using OLS (Ordinary Least Square) such as multiple linear regression analysis by looking at the relationship between ξ_j and ξ_i.

$$\xi_j = \sum_{i=1}^{I_j} \gamma_{ji} \xi_i, \tag{10}$$

$$\gamma_{ji} = (\xi_i' \xi_i)^{-1} \xi_i' \xi_j, \tag{11}$$

In reflective measurement models, loading factors are estimated such as multiple linear regression of relationships described as follows:

$$X_{jk} = \lambda_{jk} \xi_j, \tag{12}$$

$$\lambda_{jk} = \left(\xi_j' \xi_j\right)^{-1} \xi_j' X_{jk}. \tag{13}$$

2.4. PLS Algorithm Stage 3

The last stage is to estimate location parameters. There are two estimated location parameters γ_{0j} (structural model constant) and λ_{0jk} (reflective measurement model constant). The specification of an equation containing a constant is defined as a linear regression as follows:

$$E(\xi_i) = \gamma_{0j} + \sum_i^{I_j} \gamma_{ji} \xi_i, \tag{14}$$

$$E\left(\xi_j\right) = \lambda_{0jk} + \lambda_{jk} \xi_j. \tag{15}$$

The location parameter takes into account the mean of the latent variables and indicators. The mean for the estimation of latent variables is defined as follows:

$$\widehat{m_j} = \sum_{k=1}^{K_j} w_{jk} X_{jk}, \tag{16}$$

$$\hat{\xi_j} = \xi_j + \widehat{m_j}. \tag{17}$$

Based on the form of the equation above γ_{0j} and λ_{0jk} can be defined as follows [15]:

$$\gamma_{0j} = \widehat{m_j} - \sum_i^{I_j} \gamma_{ji} \widehat{m_i}, \tag{18}$$

$$\lambda_{0jk} = X_{jk} - \lambda_{jk} \widehat{m_j}. \tag{19}$$

Model evaluation is done to see indicators and variables that can work well in model analysis. Model evaluation is two, namely measurement model evaluation and structural model evaluation.

2.5. Evaluation of Measurement Models on Reflective Indicators

2.5.1. Convergent Validity

Convergent Validity is indicated by the value of the loading factor (λ). This value describes the relationship between the indicator and its latent variable. A loading factor value above 0.7 is said to be an ideal value that can work well in model analysis and is said to be significant as an indicator that measures latent variables. A loading factor value below 0.7 can be eliminated from the model [16].

2.5.2. Composite Reliability

Composite Reliability is part of the indicator that measures the relationship between latent variables. A latent variable is said to be reliable if the value of Composite Reliability is more than 0.7. Composite Reliability can be defined by the following formula [16].

$$CR = \frac{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2}{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2 + \sum_{k=1}^{K_j}(1-\lambda_{jk}^2)}. \tag{20}$$

2.6. Structural Model Evaluation

Evaluation of the structural model is carried out by looking at the estimated value of the path coefficient which describes the strength of the relationship between latent variables, R^2 which indicates the magnitude of variability of endogenous latent variables described by exogenous latent variables, and Q^2 which can be used for the predictive ability of the model. If the value of Q^2 gets closer to 1, then the model has good predictions [9]. The value R^2 and Q^2 can be described as follows:

$$R^2 = \sum_{k=1,j=1}^{K,J} \gamma_{jk}\, cor\left(\xi_k, \eta_j\right), \tag{21}$$

$$Q^2 = 1 - (1 - R_1^2)(1 - R_2^2) \ldots (1 - R_n^2). \tag{22}$$

The bootstrap sampling method involves resampling from the original sample. By resampling or repeating sampling, the bootstrap method is used to determine the average value of derivatives from skewed data [17]. The bootstrap resample approach employs hypothesis testing. The following are the suggested hypotheses.

2.6.1. The statistical hypothesis of structural models, the influence between latent variables is:

$$H_{0i}: \gamma_i = 0;\ H_{1i}: \gamma_i \neq 0$$

2.6.2. The statistical hypothesis of the measurement model is:

$$H_{0i}: \lambda_i = 0;\ H_{1i}: \lambda_i \neq 0.$$

Digital literacy is the ability to use digital technology to obtain, manage, understand, integrate, communicate, evaluate, and produce information for employment, decent work, and entrepreneurship safely and ethically. This includes skills referred to by various terms such as media literacy, information literacy, computer literacy, and ICT literacy. Digitalization in Indonesia will impact revenues of up to 150 billion US dollars by 2025 and create 3.7 million new jobs. This potential, among others, is evidenced by the increasing number of emerging start-up technology companies [18].

Education is the act, practice, or application of discipline to the intellect or a process of character training, the process of education is crucial to human development [19]. The ability to access employment, resources, and skills that enable one to not just survive but also thrive is one of the reasons why education is frequently referred to as the great equalizer. Because of this, having access to a good education is considered a known antidote to poverty. Numerous other problems that might make individuals, families, and even entire communities vulnerable to the cycle of poverty can be resolved with education [20].

Demography is the scientific study of human population growth and development, with a focus on migration, marriage, health, and living arrangements as well as factors such as fertility, mortality, and migration [21]. Over the previous few decades, poverty has substantially decreased worldwide. This shift was accompanied in many emerging nations by quick advancements in demographic outcomes, such as declining child mortality and fertility [22].

Employment is a contract of a worker will perform to an employer. In return, the worker receives a salary or wage with some negotiable terms for both parties [4]. Poverty can be anticipated if a person has a job. In all European countries, poverty will increase for the unemployed and the Great Recession brings unfavorable social repercussions due to widespread unemployment [23].

Poverty is the state or situation of an individual or society when there is a lack of means of livelihood. Individuals or communities living in poverty experience insufficient access to adequate housing, clean water, healthy food, and medical care. Poverty is not only caused by income earned, poverty can also be caused by other factors such as education, employment, and so on [24].

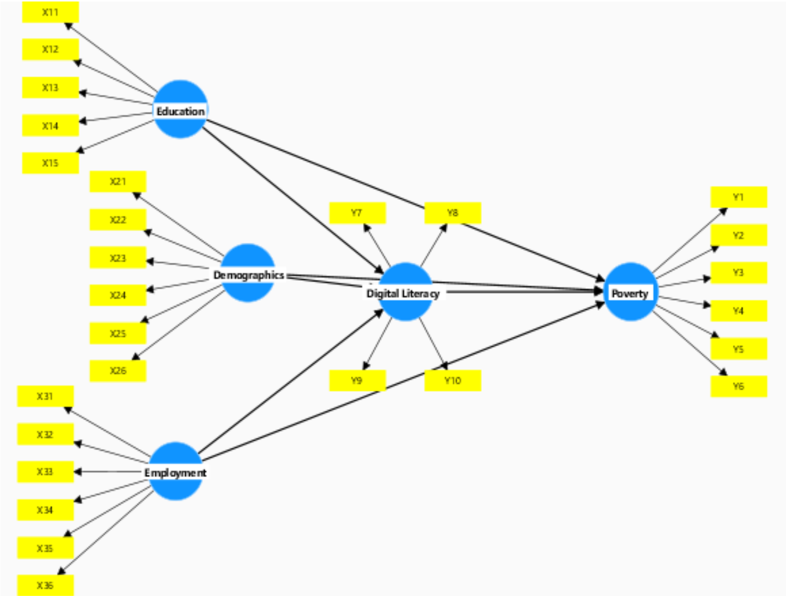

Figure. 1. Path Chart of Latent Variable and Indicator.

Table 1. Path Chart of Latent Variable and Indicator

Latent Variables	Indicators	
Education (ξ_1)	X11	Average Years of Schooling for Residents Aged 15 Years and Over
		Availability of high schools
	X12	College Availability
	X13	The number of high school students
	X14	The number of college students
	X15	
Demographics (ξ_2)	X21	Life expectancy
	X22	Population growth rate
	X23	Area
	X24	Population
	X25	Human Development Index (HDI)
	X26	Population density
Employment (ξ_3)	X31	Percentage of employed against the labor force
		Open unemployment rate
	X32	Labor force participation rate
	X33	Registered job seekers
	X34	Registered vacancies
	X35	Workforce fulfilment
	X36	

Poverty (η_1)	Y1	Provincial Minimum Wage (UMP)
	Y2	Percentage of poor people
	Y3	Poverty severity
	Y4	Depth of poverty
	Y5	Poverty line
	Y6	Provincial per capita expenditure
Digital Literacy (η_2)	Y7	Information and data literacy
	Y8	Communication and Collaboration
	Y9	Security in the use of digital technology
	Y10	Ability to use technology

2.7. Analysis Method

To see the influence between factors in this study, the author applies data analysis techniques using Structural Equation Modeling (SEM) with the Partial Least Square (PLS) method. This research uses secondary data obtained from several sources, including the Badan Pusat Statistik (BPS) and the Ministry of Communication and Information Technology of Indonesia (Kominfo). The data used are data related to education, demography, employment, digital literacy, and poverty which consists of 27 indicators and five latent variables. This data is taken from the data in 34 provinces in Indonesia in 2020. The five latent variables are education, demography, employment, digital literacy, and poverty. An explanation of latent variables and their indicators can be seen in Table 1.

The data analysis techniques in this study are as follows: (1) Descriptive statistical analysis, (2) Designing models, (3) Creating a path chart, (4) Performing a path diagram conversion to the equation, (5) Estimating parameters, (6) Evaluate the model, (7) Conducting hypothesis testing, and (8) Draw the conclusions.

3. Results

Descriptive statistics are used to describe in general the variables in the study. The results of descriptive statistics on the indicators in this study can be seen in Table 2. The value of the parameter coefficient/weight (w_{jk}) of the measurement model λ and the parameters of the structural model γ are obtained in Table 3. Evaluation of measurement models on reflective indicators includes the value of validity and reliability of each indicator against its latent variables.

This study consisted of 34 observations and 5 variables, validity tests were analyzed through degrees of freedom ($df = 34 - 5 = 29$) so that the t-table value for the significance level of 10% with two-tailed and df 29 was 1.7. Validity is a value that describes the relationship between a reflective indicator and its latent variable. The evaluation is by looking at the value of the loading factor (λ), if the value of the loading factor ($\lambda \geq 0.5$) then the indicator is declared valid. However, if the value of the loading factor ($\lambda < 0.5$) then the indicator is invalid and must be eliminated from the model. In Table 3 there are still a loading factor value ($\lambda < 0.5$) that is on the indicator X_{11}, X_{21}, X_{22}, X_{23} $X_{24}, X_{32}, X_{34}, X_{35}, X_{36}, Y_2, Y_3$, dan Y_4. The loading factor value ($\lambda < 0.5$) indicates that the indicator is invalid and must be eliminated in the next analysis. So that at the next stage of analysis the indicator $X_{11}, X_{21}, X_{22}, X_{23}, X_{24}, X_{32}, X_{34}, X_{35}, X_{36}, Y_2, Y_3$, dan Y_4 is no longer used. The models in Figures 2 and 3 are over-identified because the number of parameters of 27 is smaller than the number of data of 34. The following Figures 2 and 3 are path diagrams of the SEM-PLS model before and after eliminating invalid indicators.

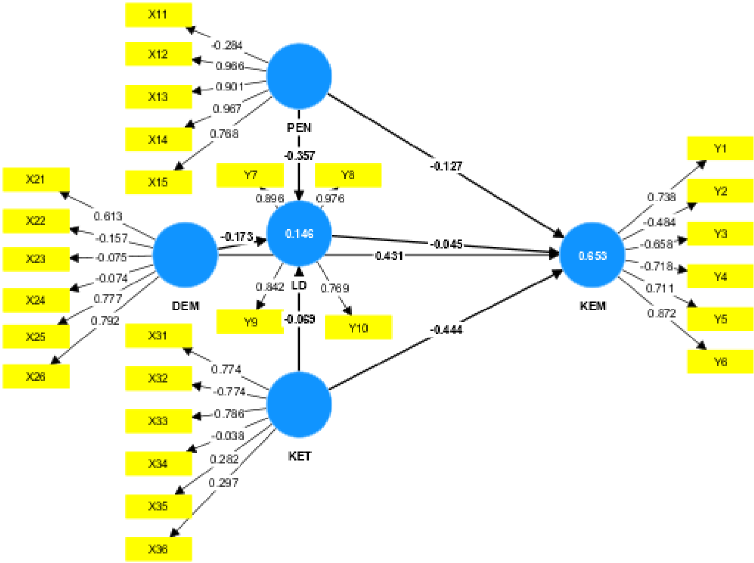

Figure. 2. Path Chart and Loading Factor Value Before Elimination of Invalid Indicators.

Table 2. Descriptive Statistics

Variable	Min	Max	Median	IQR
Poverty (η_1)				
Y_1	1704608	4276350	2678863	639170.75
Y_2	4.45	26.80	9.140	6.715
Y_3	0.09	0.72	0.280	0.2375
Y_4	0.43	2.85	1.150	0.8325
Y_5	356967	723478	504445	152280.3
Y_6	794361	1140075	1251783.76	336501
Digital Literacy (η_2)				
Y_7	2.68	3.77	3.250	0.305
Y_8	3	3.97	3.420	0.3975
Y_9	3.30	4.38	3.670	0.315
Y_{10}	3.08	4.55	3.740	0.445
Education (ξ_1)				
X_{11}	6.96	11.17	9.2	1.2675
X_{12}	107.00	5884	589	805
X_{13}	8	389	54	78.5
X_{14}	29169	2047024	167443	252433
X_{15}	11834	1308214	94760	170810
Demographics (ξ_2)				
X_{21}	65.14	75.03	70	3.0625
X_{22}	0.58	4.13	1.4	0.7075
X_{23}	664.01	319036.05	42012.890	56906.45
X_{24}	701.80	48274.20	1.590	6551.375

Table 2. Descriptive Statistics

Variable	Min	Max	Median	IQR
X_{25}	60.44	80.77	71.450	3.11
X_{26}	9	15907	104	220.5
Employment (ξ_3)				
X_{31}	89.05	96.68	94.490	2.295
X_{32}	3.32	10.95	5.630	2.295
X_{33}	63.40	74.32	68.670	4.9625
X_{34}	16765	1310894	154007	233129.5
X_{35}	8384	595499	53106	81916.25
X_{36}	6987	449249	44258	74374.5

Based on Figure 3, all loading factor values are greater or equal to 0.5 ($\lambda \geq 0.5$) for each indicator of each latent variable: education, demography, employment, digital literacy, and poverty. Based on these provisions, all indicators used are good and valid so that they can be used in measuring latent variables.

Table 3. Model Parameter Estimation

Loading Factor Measurement Model	
$\lambda_{X11} = -0.284$	$\lambda_{X34} = -0.038$
$\lambda_{X12} = 0.966$	$\lambda_{X35} = 0.282$
$\lambda_{X13} = 0.901$	$\lambda_{X36} = 0.297$
$\lambda_{X14} = 0.967$	$\lambda_{Y1} = 0.738$
$\lambda_{X15} = 0.768$	$\lambda_{Y2} = -0.484$
$\lambda_{X21} = 0.613$	$\lambda_{Y3} = -0.658$
$\lambda_{X22} = -0.157$	$\lambda_{Y4} = -0.718$
$\lambda_{X23} = -0.075$	$\lambda_{Y5} = 0.711$
$\lambda_{X24} = -0.074$	$\lambda_{Y6} = 0.872$
$\lambda_{X25} = 0.777$	$\lambda_{Y7} = 0.896$
$\lambda_{X26} = 0.792$	$\lambda_{Y8} = 0.976$
$\lambda_{X31} = 0.774$	$\lambda_{Y9} = 0.842$
$\lambda_{X32} = -0.774$	$\lambda_{Y10} = 0.769$
$\lambda_{X33} = 0.786$	

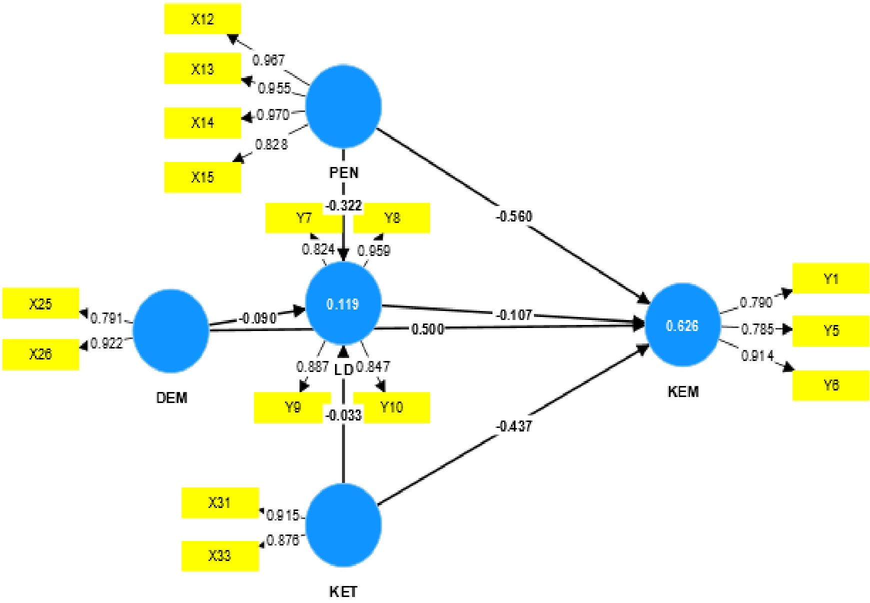

Figure. 3. Path Chart and Loading Factor Value After Elimination of Invalid Indicators.

Reliability indicates the level of consistency of the data. A variable is said to be reliable if it has a composite reliability value greater than 0.7. The composite reliability value of each latent variable can be seen in Table 4.

Table 4. Composite Reliability of Latent Variable

Variable	Composite Reliability
Education	0.963
Demographics	0.848
Employment	0.890
Digital Literacy	0.932
Poverty	0.870

Based on Table 4 the composite reliability value of each latent variable is more than 0.7. This means that all indicators of the measured latent variable are declared reliable. Based on these criteria, it can be concluded that the measurement model is good because it has met the validity test and reliability test.

Table 5. Values of R-square, Q-square, and F-square

Evaluation Size	Value
R_1^2	0.626
R_2^2	0.119
Q^2	0.671
Variable	**F-square**
Education → Digital Literacy	0.099
Demographics → Digital Literacy	0.007
Employment → Digital Literacy	0.001
Education → Poverty	0.644
Demographics → Poverty	0.489
Employment → Poverty	0.354
Digital Literacy → Poverty	0.027

Structural model evaluation can be done to see the relationship between latent variables and their effects by looking at the value of the estimated result coefficient and the level of significance. Measures for the evaluation of structural models can use values of R-square and Q-square.

Table 5 indicates the value of $R_1^2 = 0.626$ for the variables of poverty, meaning that the poverty variable that can be explained by education, demographics, employment, and digital literacy variables is 62.6 percent. The remaining 37.4 percent was explained by other variables not mentioned in the model. The digital literacy variable value $R_2^2 = 0.119$ means that the 11.9 percent digital literacy variable can be explained by education, demographic, and employment variables. The remaining 88.1 percent was explained by other variables not included in the study. The resulting value of Q^2 is 0.671, meaning that the model has a good prediction because the value of Q^2 is close to 1.

Evaluation of the model is also seen based on discriminant validity, this value is seen based on three categories: cross-loading, HTMT, and Fornell Larcker. These values can be seen in Tables 6, 7, and 8.

Table 6 shows valid values for all variables because the indicator values on the value-bound variables are greater than the values of other indicators. Table 7 is valid because all values are less than 0.9. Table 8 is valid because the value of the relationship to the same latent variable is greater than the other values.

Bootstrapping is used to determine the standard deviation/standard error in determining the significance of statistical values without relying on any assumptions [25]. This bootstrapping technique involves the main sample to be resampled. This method aims to find statistics in the distribution of data [17]. The bootstrapping procedure is performed using 500 resampling at a t-table value of 1.65 (2-tailed) and a significant level of 0.1. The hypotheses used are:

$H_0: \lambda_i = 0$

$H_1: \lambda_i \neq 0.$

The results of t-statistical testing for measurement models can be seen in Table 9. In the Table 9 shows a good measurement model for each of the latent variables obtained. This is indicated by a t-statistic value greater than 1.65 (2-tailed) at a significant level of 0.1 or with a p-value less than 0.1. The hypothesis used for the measurement model is $H_{0i}: \lambda_i = 0$ and $H_{1i}: \lambda_i \neq 0$. The model shows that $\lambda_i \neq 0$ meaning the hypothesis H_{0i} is rejected and we agree with the alternative hypothesis H_{1i}, meaning that there is an influence between the latent variable and the indicator. Based on this hypothesis, we can conclude that each latent variable has a relationship with its indicators and has path coefficient values that are all positive. The smallest contribution was indicator Y5 with a coefficient to the latent variable of poverty is 0.785; the largest contribution was indicator X14 with a path coefficient to the latent variable of education is 0.970. The path coefficient values for each bootstrap resampling in Table 10 show the same value as the value of the actual path coefficient.

Table 6. Values of Cross-Loading

Variable	ξ_2	η_2	ξ_1	ξ_3	η_1
Poverty (η_1)					
Y_1	0.323	-0.067	-0.397	-0.367	**0.790**
Y_5	0.231	0.036	-0.283	-0.233	**0.785**
Y_6	0.707	-0.082	0.015	-0.533	**0.914**
Digital Literacy (η_2)					
Y_7	-0.0938	**0.824**	-0.414	-0.020	0.109
Y_8	-0.090	**0.959**	-0.323	0.065	-0.011
Y_9	-0.195	**0.887**	-0.219	0.154	-0.175
Y_{10}	-0.209	**0.847**	-0.224	0.256	-0.135
Education (ξ_1)					

Table 6. Values of Cross-Loading

Variable	ξ_2	η_2	ξ_1	ξ_3	η_1
X_{12}	0.123	-0.309	**0.967**	-0.269	-0.334
X_{13}	0.462	-0.336	**0.955**	-0.410	-0.085
X_{14}	0.154	-0.241	**0.970**	-0.277	-0.317
X_{15}	0.442	-0.386	**0.828**	-0.485	0.010
Demographics (ξ_2)					
X_{25}	**0.791**	-0.034	0.236	-0.456	0.389
X_{26}	**0.922**	-0.219	0.273	-0.423	0.565
Employment (ξ_3)					
X_{31}	-0.559	0.098	-0.496	**0.915**	-0.484
X_{33}	-0.317	0.145	-0.146	**0.876**	-0.389

Table 7. Values of HTMT

Variable	ξ_2	η_2	ξ_1	ξ_3	η_1
Demographics (ξ_2)					
Digital Literacy (η_2)	0.219				
Education (ξ_1)	0.398	0.369			
Employment (ξ_3)	0.706	0.178	0.437		
Poverty (η_1)	0.668	0.146	0.376	0.583	

Table 8. Values of Fornell Larcker

Variable	ξ_2	η_2	ξ_1	ξ_3	η_1
Demographics (ξ_2)	0.859				
Digital Literacy (η_2)	-0.169	0.881			
Education (ξ_1)	0.297	-0.337	0.932		
Employment (ξ_3)	-0.500	0.133	-0.375	0.896	
Poverty (η_1)	0.571	-0.061	-0.212	-0.491	0.832

Table 9. Results of T-Statistical Values of Loading Measurement Model

	Loading Factor	*T-Statistic*	*P-value*
Education			
X_{12}	0.967	8.281	0.000
X_{13}	0.955	6.683	0.000
X_{14}	0.970	8.282	0.000
X_{15}	0.828	4.632	0.000
Demography			
X_{25}	0.791	3.185	0.002
X_{26}	0.922	3.684	0.000

Table 9. Results of T-Statistical Values of Loading Measurement Model

	Loading Factor	*T-Statistic*	*P-value*
Employment			
X_{31}	0.915	4.100	0.000
X_{33}	0.876	4.714	0.000
Poverty			
Y_1	0.790	6.085	0.000
Y_5	0.785	5.711	0.000
Y_6	0.914	3.367	0.001
Digital Literacy			
Y_7	0.824	6.006	0.000
Y_8	0.959	9.689	0.000
Y_9	0.887	7.349	0.000
Y_{10}	0.847	6.436	0.000

Table 10. Bootstrap Resampling Estimation Results of Path Coefficient Value

Variable	Path Coefficient	Bootstrap Resampling (Path Coefficient)		
		100	500	1000
Education → Digital Literacy	-0.322	-0.322	-0.322	-0.322
Demographics → Digital Literacy	-0.090	-0.090	-0.090	-0.090
Employment → Digital Literacy	-0.033	-0.033	-0.033	-0.033
Education → Poverty	-0.560	-0.560	-0.560	-0.560
Demographics → Poverty	0.500	0.500	0.500	0.500
Employment → Poverty	-0.437	-0.437	-0.437	-0.437
Digital Literacy → Poverty	-0.107	-0.107	-0.107	-0.107

Mathematically the structural model of PLS analysis can be written as follows:

$$\eta_1 = -0.560\,\xi_1 + 0.500\,\xi_2 - 0.437\,\xi_3 - 0.107\,\eta_2 + \zeta_1 \qquad [23]$$

$$\eta_2 = -0.322\,\xi_1 - 0.090\,\xi_2 - 0.033\,\xi_3 + \zeta_2 \qquad [24]$$

Based on Table 11, the t-statistics value at 500 resampling has a greater value on most of the relationships between variables compared to other resampling, so 500 resampling is best used in subsequent analyses. The results of bootstrapping t-statistics resampling testing using 500 resamplings are shown in Table 12.

Table 11. Bootstrap Resampling Estimation Results T-Statistic

Variable	Resampling Bootstrap (T-Statistics)		
	100	500	1000
Education → Digital Literacy	1.216	1.235	1.225
Demographics → Digital Literacy	0.381	0.425	0.428
Employment → Digital Literacy	0.128	0.128	0.124
Education → Poverty	2.805	3.700	3.404
Demographics → Poverty	1.013	1.056	1.016

Employment → Poverty	3.169	2.888	2.666
Digital Literacy → Poverty	1.053	1.028	0.986

Table 12. Value of Loading Factor, T-Statistic, and P-Value used Bootstrap

Variable	*Loading Factor*	*T-Statistic*	*P-value*
Education → Digital Literacy	-0.322	1.235	0.218
Demographics → Digital Literacy	-0.090	0.425	0.671
Employment → Digital Literacy	-0.033	0.128	0.898
Education → Poverty	-0.560	3.700	0.000*
Demographics → Poverty	0.500	1.056	0.292
Employment → Poverty	-0.437	2.888	0.004*
Digital Literacy → Poverty	-0.107	1.028	0.305

Based on Table 11, the t-statistics value at 500 resampling has a greater value on most of the relationships between variables compared to other resampling, so 500 resampling is best used in subsequent analyses. The results of bootstrapping t-statistics resampling testing using 500 resamplings are shown in Table 12.

The results of bootstrapping t-statistics resampling testing using 500 resamplings are shown in Table 12. Based on Table 12 the causal relationships between latent variables are described as follows:

$H_1: \gamma_{11} \neq 0$. Education (ξ_1) affects digital literacy (η_2). The t-statistics value of 1.235 is smaller than the t-table of 1.65 and the p-value of 0.218 is greater than 0.1 (not significant), meaning that education has an influence on digital literacy with a negative influence of -0.322 but not significant.

$H_2: \gamma_{21} \neq 0$. Demographics (ξ_2) affect digital literacy (η_2). The t-statistics value of 0.425 is smaller than the t-table of 1.65 and the p-value of 0.671 is greater than 0.1 (not significant), meaning that demographics influence digital literacy with a negative influence of -0.090 but not significant.

$H_3: \gamma_{31} \neq 0$. Employment (ξ_3) affects digital literacy (η_2). The t-statistics value of 0.128 is smaller than the t-table of 1.65 and the p-value of 0.898 is greater than 0.1 (not significant), meaning that employment has an influence on digital literacy with a negative influence of -0.033 but not significant.

$H_4: \gamma_{12} \neq 0$. Education (ξ_1) affects poverty (η_1). The t-statistics value of 3.700 is greater than the t-table of 1.65 and the p-value of 0.000 is less than 0.1 (significant), meaning that education has an influence on poverty with a negative influence of -0.560 and significant.

$H_5: \gamma_{22} \neq 0$. Demographics (ξ_2) affect poverty (η_1). The t-statistics value of 1.056 is smaller than the t-table 1.65 and the p-value of 0.292 is greater than 0.1 (not significant), meaning that demographics influence poverty with a positive influence of 0.500 but not significant.

$H_6: \gamma_{32} \neq 0$. Employment (ξ_3) affects poverty (η_1). The t-statistics value of 2.888 is greater than the t-table of 1.65 and the p-value of 0.004 is smaller than 0.1 (significant), meaning that employment has an influence on poverty with a negative influence of -0.437 and significant.

$H_7: \gamma_4 \neq 0$. Digital literacy (η_2) affects poverty (η_1). The t-statistics value of 1.028 is smaller than the t-table of 1.65 and the p-value of 0.305 is greater than 0.1 (not significant), meaning that digital literacy has an influence on poverty with a negative influence of -0.107 but not significant.

Poverty (η_1) is influenced by education (ξ_1) with a loading factor of -0.560, and employment (ξ_3) with a loading factor of -0.437. That is, if education increases by one unit while assuming permanent employment, then poverty decreases by 0.560. In addition, if employment increases by one unit assuming permanent education, then poverty decreases by 0.437. No variable has a significant effect on digital literacy and there is no significant effect of digital literacy in mediating the Influence of Education, Demography, and Employment on Poverty in Indonesia.

The results of this research are similar to those conducted by Zhou, et al., according to this research, digital literacy can reduce poverty by increasing the performance and scale of entrepreneurship. Digital literacy is no less important than employment [26]. This study has an important impact on understanding and improving the governance framework for long-term poverty alleviation through digital literacy.

4. Conclusions

The poverty modeling in Indonesia with education, demographics, and employment as factors as well as digital literacy as mediating variables using the PLS approach obtained results that for the measurement model there are indicators that have met the criteria of validity and reliability. The indicators include four indicators of education variables (ξ_1) namely the availability of high school, college availability, the number of students at the high school, and the number of College-level students; two indicators of demographic variables (ξ_2) namely the Human Development Index (HDI) and population density; two indicators of employment variables (ξ_3) namely the percentage of employment to the labor force and the labor force participation rate; three variable indicators of poverty (η_1) namely the Provincial Minimum Wage (UMP), poverty line, and provincial per capita expenditure; and four variable indicators of digital literacy (η_2), namely information and data literacy, communication and collaboration, security in the use of digital technology, and the ability to use technology.

Based on the factoring scheme, the variation in the poverty model (η_1) that can be explained by education, demographics, employment, and digital literacy variables is 62.6 percent, the remaining 37.4 percent is explained by other variables not mentioned in the model. While the variation in the digital literacy model (η_2) that can be explained by education, demographic, and employment variables is only 11.9 percent, the remaining 88.1 percent is explained by other variables not mentioned in the model. The formed structural model is as follows:

$$\eta_1 = -0.560\,\xi_1 + 0.500\,\xi_2 - 0.437\,\xi_3 - 0.107\,\eta_2 + \zeta_1 \tag{25}$$

$$\eta_2 = -0.322\,\xi_1 - 0.090\,\xi_2 - 0.033\,\xi_3 + \zeta_2 \tag{26}$$

The recommendation that can be given based on the results of this research analysis is: that the Indonesian government needs to consider factors found to be significant in reducing poverty. Improving all factors of education and employment will effectively reduce poverty because these variables and poverty variables have an inverse and significant relationship.

Ethics approval

The research has met research ethical rules so that it can be carried out without harm to the research subjects.

Competing interests

All the authors declare that there are no conflicts of interest.

Funding

This study received no external funding.

Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

References

[1] Central Agency of Statistics (BPS), 'Badan Pusat Statistik', 2023. [Online]. Available: https://www.bps.go.id/subject/23/kemiskinan-dan-ketimpangan.html#subjekViewTab1.

[2] United Nations Development Programme (UNDP), 'Sustainable Development Goals', 2023. [Online]. Available: https://www.undp.org/sustainable-development-goals.

[3] A. Klimczuk, ‘Introductory Chapter: Demographic Analysis’, Demographic Analysis: Selected Concepts, Tools, and Applications, p. 3, 2021.

[4] S. M. Heathfield, ‘Why Human Resources Management Is So Important’, The Balance Careers, 2020.

[5] D. R. A. Schallmo and C. A. Williams, ‘Digital Transformation Now! Guiding the Successful’, 2018.

[6] Nurhafifah, S. Mahdi, and R. Oktavia, Analisis Faktor yang Saling Memengaruhi Kemiskinan di Indonesia Menggunakan Metode Structural Equation Modeling-Partial Least Square (SEM-PLS). Banda Aceh: Universitas Syiah Kuala, 2023.

[7] R. Parianom, I. Arrafi, and D. Desmintari, ‘The Impact of Digital Technology Literacy and LifeSkills On Poverty Reduction’, Devotion: Journal of Research and Community Service, vol. 3, no. 12, pp. 2002–2007, 2022.

[8] R. H. Hoyle, ‘The structural equation modeling approach: Basic concepts and fundamental issues’, 1995.

[9] M. Sarstedt, C. M. Ringle, and J. F. Hair, ‘Partial least squares structural equation modeling’, in Handbook of market research, Springer, 2021, pp. 587–632.

[10] C. M. Stein, N. J. Morris, and N. L. Nock, ‘Structural equation modeling’, Statistical human genetics: Methods and protocols, pp. 495–512, 2012.

[11] R. Solling Hamid and S. M Anwar, ‘Structural Equation Modeling (SEM) Berbasis Varian’. PT Inkubator Penulis Indonesia, 2019.

[12] P. H. Garthwaite, ‘An interpretation of partial least squares’, Journal of the American Statistical Association, vol. 89, no. 425, pp. 122–127, 1994.

[13] M. Tenenhaus, V. E. Vinzi, Y.-M. Chatelin, and C. Lauro, ‘PLS path modeling’, Computational statistics & data analysis, vol. 48, no. 1, pp. 159–205, 2005.

[14] G. S. Trujillo, ‘Pathmox approach: Segmentation trees in partial least squares path modeling’, Universitat Politècnica de Catalunya (UPC), 2009.

[15] A. Anekawati, B. W. Otok, and Others, ‘Structural equation modelling with three schemes estimation of score factors on partial least square (Case study: the quality of education level SMA/MA in Sumenep Regency)’, in Journal of Physics: Conference Series, 2017, vol. 855, p. 012006.

[16] W. W. Chin and Others, ‘The partial least squares approach to structural equation modeling’, Modern methods for business research, vol. 295, no. 2, pp. 295–336, 1998.

[17] F. P. A. P. Rachman, R. Goejantoro, and M. N. Hayati, ‘Penentuan Jumlah Replikasi Bootstrap Menggunakan Metode Pretest Pada Independent Sampel T Test’, EKSPONENSIAL, vol. 9, no. 1, pp. 35–40, 2018.

[18] A. Das, M. Chowdhury, and S. Seaborn, ‘ICT diffusion, financial development and economic growth: new evidence from low and lower middle-income countries’, Journal of the Knowledge Economy, vol. 9, pp. 928–947, 2018.

[19] P. O. Adesemowo and O. A. Sotonade, ‘Basic of education: The meaning and scope of education’, Olabisi Onabanjo University, 2022.

[20] O. Giovetti, ‘How does education affect poverty? It can help end it. Concern Worldwide’. 2022.

[21] N. J. Spence, ‘Family Demography’, in Encyclopedia of Gerontology and Population Aging, Springer, 2022, pp. 1789–1792.

[22] F.-B. Wietzke, ‘Poverty, inequality, and fertility: the contribution of demographic change to global poverty reduction’, Population and Development Review, vol. 46, no. 1, pp. 65–99, 2020.

[23] M. Vaalavuo and O. Sirniö, ‘Jobs against poverty: a fixed-effects analysis on the link between gaining employment and exiting poverty in Europe’, European Societies, vol. 24, no. 4, pp. 431–462, 2022.

[24] J. Chen, ‘What’s Poverty? Meaning, Causes, and How to Measure’. 2023.

[25] J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer Nature, 2021.

[26] D. Zhou, F. Zha, W. Qiu, and X. Zhang, 'Does digital literacy reduce the risk of returning to poverty? Evidence from China', Telecommunications Policy, vol. 48, no. 6, p. 102768, 2024.