

International Journal of
Engineering Research and Science & Technology



ISSN : 2319-5991

www.ijerst.com

Email: editor@ijerst.com or editor.ijerst@gmail.com

c This article can be downloaded from <http://www.ijerst.com/currentissue.php>

Partial Least Square Non-Linear Structural Equation Modelling for Cardio Vascular Disease

1Xavier.S,2LeoAlexander.T

Abstract: Structural Equation Modelling (SEM) is used to examine the relationships between the constructs. Partial Least Square nonlinear Path Modeling is another name for it (PLS- PM). PLS-PM uses a partial least squares algorithm to estimate factor scores and path coefficients. Two linear and two non-linear constructs are used to examine the Ejection Fraction and Survival of cardiovascular disease data in this research. In order to study the interrelationships between the various constructions, an inner model and an exterior model must be created. PLS-SEM is used to estimate the parameters of the provided models in R version 3.5.1.

Key Words: Structural equation modeling using partial least squares Modeling the inside out, a model of the outside world, Ejection Fraction, Nonlinear Effect, and Linear Effect The R language.

1. INTRODUCTION

Testing the link between the constructs is done by using the PLS Structural Equation Modelling (PLS SEM). Both a simple model and a complicated model are possible. Partial least squares for principal component analysis was explained by Wold (1975a) in a seminar paper. In 1982 and 1985, Wold detailed the phases of the algorithm for PLS-PM. Authors Chin (1998) and Tenenhaus et al. (2005) have presented further developments on the PLS method to Structural Equation Models following Wold's original proposal. An iterative approach that solves the blocks of each model separately is employed. A regression model's latent and manifest variables can both be explained by PLS-PM, which claims to do so at its best in terms of residual variance (Fornell and Bookstein measurement. Empirical confidence intervals

and hypothesis testing procedures using resampling methods (Chin 1998; Tenenhaus et al. 2005) such as Jackknife and bootstrap are used in place of the classical parametric inferential framework in PLS-PM. As a result, the estimates have less ambitious statistical features, such as recognized bias in coefficients but broad consistency (Cassel et al. 1999, 2000).

Section 2 of this study discusses data characteristics, while Section 3 of the document discusses the pls-sem model formulation. Section 4 explains the technique for the partial least square algorithm. Measurement and structural models' quality indices are shown below. Section 6 provides the findings of the PLS-PM application to the cardiovascular disease data.

1AssistantProfessor,DepartmentofStatistics,LoyolaCollege,Chennai-34,sxavierloyola@gmail.com

2AssociateProfessor,DepartmentofStatistics,LoyolaCollege, Chennai-34,leoalex.62@gmail.com

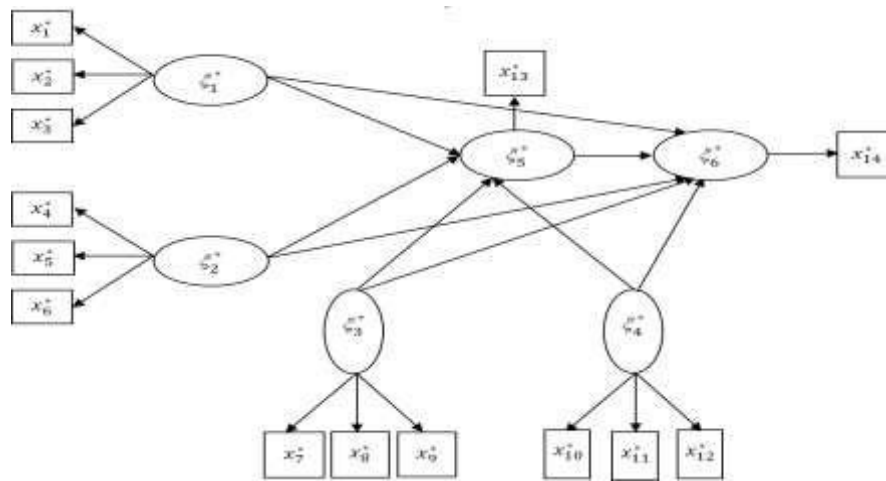
Correspondence AuthorDr. T. Leo Alexander, Associate Professor, Department of Statistics, Loyola College, Chennai 600034. Mail:leoalex.62@gmail.com

2. DATA CHARACTERISTIC

In Chennai City, a patient with Cardio Vascular Disease is being studied. A total of 405 samples are gathered from private hospitals in Chennai for this study. In the clinical laboratory, information on 13 different patient factors was collected, including the patient's name, gender, age, BMI, where they live (urban or rural), smoking and drinking habits, and family history. The patients' BGL, BCL, BP, and EF, as well as their survival status, were all measured during the study..

3. The PLS-SEM Model Specification

Based on partial least square approach, we have considered two measurement models



namely

latent measurement model and nonlinear latent measurement model which are exhibited in Diagram 1.

3.1 Structural Model

Blood factor and lifestyle 1 2 factor are two latent exogenous variables in the linear structural equation model, as well as latent quadratic and latent endogenous variables.

3.2 1, 2, 3, 1, 4, and 5

3.3 and .. Three manifest variables, namely blood glucose (x1), blood pressure, and heart rate, are used to calculate the blood factor ().

3.4 6 1

3.5 Blood pressure and cholesterol are two of the three. Three obvious elements

serve as indicators of one's way of life, called the lifestyle factor ().

3.6 (x4), (x5), and (x6) have a history of smoking, drinking, or both. linear influence of and on the route coefficients

3.7 1 2 3 4 5 6

3.8 It is the quadratic effect of the latent effect of that is the notation for this interaction effect, which is referred to by the notation.

3.9 2 13 3 14 4

3.10 is a variable that is internal to the organism. is a measure of the impact of on . There are no non-linear effects on the parameters.,.

3.11 5 5 6 5 6

3.12 a number between twenty-one and twenty-two

3.13 quadratic effect of quadratic effect of quadratic influence of quadratic effect of quadratic effect

3.14 1 2 23 3 24 4

3.15 unobserved, unmeasured, or unobserved factor

3.16 Two linear terms, one interaction term, one quadratic term, and two endogenous constructs are used in a

nonlinear PLS-SEM technique. Based on these, we've created a graphic representation of the model, as shown in Diagram 1. Diagram 1 A Partial Least Square Nonlinear structural equation model consists latent linear criterion ξ^* and ξ^* , a latent

1 2
interaction term ξ^* and a latent quadratic term ξ^*
and latent endogenous variables ξ^* and ξ^*
3 4 5 6

Partial least square structural equation modeling allows for the estimation of the ejection % by observing the interaction and quadratic effects. The structural or inner model and the measurement or outer model make up the PLS Path Model. It is the structural model that deals with how the latent variables are linked together. The association between the latent variables and the block of manifest variables is constructed in the measurement model.

Table 1

	ξ^*_1	ξ^*_2	ξ^*_3	ξ^*_4	ξ^*_5	ξ^*_6
ξ^*_1	1	0	0	0	1	1
ξ^*_2	0	1	0	0	1	1
ξ^*_3	0	0	1	0	1	1
ξ^*_4	0	0	0	1	1	1
ξ^*_5	0	0	0	0	0	1
ξ^*_6	0	0	0	0	0	0

The structural equation modelling for the specific model is constructed in the following equation.

$$Y = YB + \delta,$$

where Y is the matrix of latent exogenous and endogenous variables, B is the coefficient matrix and the error δ is assumed to be centred, that is $E(\delta) = 0$ and $V(\delta) = 1$.

3.17 The measurement model

For this example, let us assume that there are 'p' variables that are measured on 'n' observations, and the variables are separated into 'q' blocks. This is the dataset, which has N observations and P variables, so we'll call it "X." X is a matrix of dimensions nxp. Each block of the dataset X can be broken down into the q blocks listed above in an order of mutual exclusion. A total of three variables are present in each of the blocks listed above, however only one variable is present in each of blocks X5 and X6. Unobserved variables are associated with each block X_{pq} (where X_{pq} is the pth variable in the qth block; $q = 1, 2, 3, \dots, Q$). Diagram 1 depicts the theoretical model's structural relationship, and the adjacency matrix D is generated from this. Latent variable is the one whose entry d_{ij} equals 1.

antecedent to the latent variable. Table 1a displays the resulting matrices for the model as supplied, as seen below.

Latent constructs and their manifest variables form an outer model or measurement. All of the manifest variables that are linked to a single latent variable are grouped together as a block in the outer model, which is composed of reflective a blocks. Reflective models believe latent constructs to be the root of manifest variables. Latent constructs are not included in the model. There are two parts to this equation: the loading and the

measurement error. The loading represents the amount of data that is being loaded into the manifest variable at the start of the measurement, and the measurement error represents how much data is actually being loaded into that variable at the end of the measurement. As correlations between each manifest and its related latent variable are represented by standardized loadings, they are generally favored for interpretation purposes. According to this model's assumptions, the latent variable of the q th block has zero mean and is not linked with error pq . The following equation expresses the linear relationships in a standard regression perspective. $(x_{pq}/\xi^*) = p_0 + p_{q1} \xi^* + \dots + p_{qQ} \xi^* + \epsilon_{pq}$.

This assumption, defined as predictors specification, assures desirable estimation properties in classical Ordinary Least Squares modelling.

3.17.1 Reflective measurement

In this measurement, each block of manifest variables reflects its latent variable and can be written as the multivariate regression $Xq = \xi^* w^T + \epsilon$, where ϵ is the measurement error.

So, w^T can be estimated by least squares as

$$w^T = (T^T T)^{-1} T^T X$$

$$w = (T T^T)^{-1} T X$$

$$w = (T T^T)^{-1} T X$$

Table 2

	ξ^*_1	ξ^*_2	ξ^*_3	ξ^*_4	ξ^*_5	ξ^*_6
x_{11}	1	0	0	0	0	0
x_{21}	1	0	0	0	0	0
x_{31}	1	0	0	0	0	0
x_{42}	0	1	0	0	0	0
x_{52}	0	1	0	0	0	0
x_{62}	0	1	0	0	0	0
x_{73}	0	0	1	0	0	0
x_{83}	0	0	1	0	0	0
x_{93}	0	0	1	0	0	0

$$w = (T T^T)^{-1} T X$$

The partial least square algorithm estimates all the latent variables ξ^* , $q=1,2,3,\dots,Q$, as a linear combination of their manifest variables under the constraint to have unit variance. We assumed all the manifest variables to be scaled to zero mean and unit variance.

3.17.2 Weight matrix

When all the latent variables in the model are measured reflectively, it is called a reflective model. Let $p \in \{1,2,3,\dots,P\}$ be a set of indices for manifest variables related to latent variable ξ^* so that $w_p = (x_{p1}, x_{p2}, \dots, x_{pQ})^T$ is a column vector of length $|p|$. The outer weight matrix W can be written as follows

$$W = \begin{bmatrix} w_1 & w_2 & \dots & w_Q \end{bmatrix}$$

Table 2 represents the adjacency matrix M for the measurement model. It has the same structure as the matrix of outer weights W as it is used for the initialization. If the entry $m_{pq} = 1$ then manifest variable p is one of the indicators of the latent variable ξ^*_q .

x_{104}	0	0	0	1	0	0
x_{114}	0	0	0	1	0	0
x_{124}	0	0	0	1	0	0
x_{135}	0	0	0	0	1	0
x_{146}	0	0	0	0	0	1

3.17.3

Block Homogeneity and unidimensionality

There must be a single latent variable represented by the manifest variables in a one-dimensional space. Block homogeneity and unidimensionality can be used to identify a one-dimensional space. Cronbach's alpha, Dillion-Goldstein, and Principal component analysis of a block are used to test the homogeneity and unidimensionality of a block.

4. The partial least square algorithm

Woldin and Lohmoller invented this method in 1982 and refined it in 1989. Listed below are the five steps.

Stage 1.

The weighted sum of manifest variables is used to generate each latent variable in this stage. In this case, let us assume that all of the manifest variables are scaled so that the mean of x_{pq} is zero and the variance of x_{pq} is one. In the initialization of weights, all of the weights are assigned a value of 1. Despite the fact that the latent variables are all centred, they must still be scaled so that they all have the same variance $\hat{\Lambda} = M$

$\hat{\Lambda}^*$

$\hat{\Lambda}^* = g$, where $q=1,2,3,...,Q$.

$q \sqrt{\text{var}(\hat{\Lambda}^*)}$

The latent variables are initialized, so that we get

$\hat{\Lambda} = (\hat{\Lambda}_1^*, \dots, \hat{\Lambda}_Q^*)$.

1 Q

Stage 2. The inner approximation is made in this stage which does to estimate each latent variable as a weighted sum of its neighbouring latent variables. Again we are scaling the recomputed latent variables to have unit variance.

$\hat{\Lambda} \sim B \hat{\Lambda}$,

where B is the matrix of

inner weights, therefore $\hat{\Lambda}^* \sim$ estimation $\hat{\Lambda} = (\hat{\Lambda}_1^*, \dots, \hat{\Lambda}_Q^*)$.

$\hat{\Lambda}^* \sim$

$= g$

, where $q=1,2,3,...,Q$. We obtain the inner $\sqrt{\text{var}(\hat{\Lambda}^*)}$

1 Q

Stage 3. Outside approximation is completed at this point. As a result of Stage 2, the weights are computed from the inner approximation for the initialization. Measurement models (reflective models) of the latent variables are used to estimate the weights. A coefficient of multivariate regression in which the block of manifest variables is treated as the response variable and the latent variable as an regressor. Here's how it's explained:

$W^T T = (\hat{\Lambda}^* T^T)^{-1}$

-1

$X = \text{cov}(q, Xq)$.

Stage 4. The blocks $X_1, X_2, X_3, \dots, X_Q$ are arranged in matrix X , and the outer weights vectors $w_1, w_2, w_3, \dots, w_Q$ are arranged as outer weights matrix W . These matrices are used to estimate the factors scores by means of the manifest variables

$\hat{\Lambda}$

$\hat{\Lambda} = XW$ and $\hat{\Lambda} = g$

, where $\hat{\Lambda} = (\hat{\Lambda}_1^*, \hat{\Lambda}_2^*, \dots, \hat{\Lambda}_Q^*)$.

$q \sqrt{\text{var}(\hat{\Lambda})}$

1 2 Q

Stage 5. If the relative change of all the outer weights from one iteration to the next is smaller than a pre-defined tolerance

$$w^{pq}(\text{old}) - w^{pq}(\text{new})$$

|

$$w^{pq}(\text{new})$$

$$| < \text{tolerance}$$

for all $k=1,2,3,\dots,K$ and $q=1,2,3,\dots,Q$. The convergence is attained at the threshold value or tolerance value 1.10⁻⁵. The weighting scheme: Centroid weighting scheme, Factorial weighting scheme, and Path weighting scheme are all examples of partial least square algorithm weighting schemes. Wold proposed the Centroid approach in 1982, and later Lohmoller introduced Factorial and Path weighting schemes in 1989, respectively. Adjacency matrix D for latent variables is shown in Table 1, where D represents directionality. There is an arc from node i that moves toward the arc's head, which is node j , for any $d_{ij} = 1$. Inner weights are calculated using the adjacency matrix D . As a matrix product of the outer estimate and the matrix of inner weights E , the inner estimate ($\hat{\eta}$) is expressed. $\hat{\eta} = \hat{\xi} E^T$

Furthermore, let us denote $R = \text{cor}(\hat{\eta}^T)$, the empirical correlation matrix for the latent variables resulting from the outer estimation and $C = D + D^T$ as symmetrical matrix.

Centroid weighting scheme: Following the centroid weighting scheme, the matrix of inner weights E takes the form

e_{ij}

$$= \begin{cases} \text{sig}(r_{ij}), & \text{for } c_{ij} = 1, i, j = 1, 2, 3, \dots, Q. \\ 0, & \text{otherwise} \end{cases}$$

Factorial weighting scheme: The factorial weighting scheme

$$= \begin{cases} 1, & \text{for } i = j, i, j = 1, 2, 3, \dots, Q. \\ 0, & \text{otherwise} \end{cases}$$

0 , h

This scheme is similar to the centroid weighting scheme but, there is no sign of the correlation between two neighbouring latent variables. This might be quite reasonable when there are pairs of neighbouring latent variables with correlations nearing to zero.

Path weighting scheme: In this model, the latent variable's predecessors and successors play a different role in the relationship. The set of arrow tails leading from the successor is defined as a node. In the same way, the set of arrows going to a node's predecessor is its predecessor set. A head is the arc's first node, while a tail is its last. To determine the association between one specific latent variable and its successor, it is used in a multiple regression.

$$\hat{\eta}_i = \gamma_i + \sum_{j \in \text{pred}(i)} \gamma_{ji} \hat{\eta}_j, \quad [z] = 0, \quad i = 1, 2, 3, \dots, Q, \quad i \neq j$$

with $\text{pred}(i)$ the predecessor set of the latent variable η_i . Let $\text{succ}(i)$ be the successor set of the latent variable η_i .

γ_{ji} the element of the inner weight matrix E are

$$\gamma_{ji} = \begin{cases} \gamma_{ji}, & \text{for } j \in \text{pred}(i) \\ 0, & \text{otherwise} \end{cases}$$

, for $j \in \text{succ}(i)$

$$\gamma_{ji} = \begin{cases} \text{co}(\hat{\eta}_i, \hat{\eta}_j), & \text{for } j \in \text{succ}(i) \\ 0, & \text{otherwise} \end{cases}$$

Estimation of parameters: Once the factors scores are estimated by the partial least square algorithm, the path coefficients to be estimated by using the ordinary least square method according to the structural model. For

each latent variable η_i

, where $q = 1, 2, 3, \dots, Q$, the path coefficient is the regression coefficient on its

predecessor set $\mathcal{P}$

$$\Lambda^* p T^* \Lambda^*$$

$$-1^* p T^* \Lambda^*$$

$$\beta q = (\beta q$$

$$q)$$

$$q \quad q$$

We obtain the elements b^{ij} , $i, j = 1, 2, 3, \dots, Q$ of the estimated matrix of the path coefficients B^* ,

$$\beta^{ij} = \{$$

$$\beta^{ij}$$

$$, \quad \text{for } j \in \mathcal{P}$$

$$0, \quad \text{otherwise.}$$

The matrix B^* be interpreted as a transition matrix for the structural model.

5. The Quality indices

No global fit indicators exist in partial least square modeling, but it is important to validate the measurement, structural, and overall models separately. Fit indices such as the communality index, the redundancy index and the goodness of fit are all supported by PLS-SEM.

Communality index:
For each q th block in the model with more than one manifest variable, the quality of the measurement model is assessed by means of the communality index Pg

$$1 \quad co = \sum \text{corr}^2(x$$

$$, \Lambda^*), \text{ for all } q:$$

$$> 1.$$

$$q \quad Pq$$

$$p = 1$$

$$pq \quad q \quad q$$

Communality index explains how much of the manifest variables variability in the q th block by their own latent

variables scores Λ^*

. The communality in the q th block is a average of the squared correlations between each manifest variable and the corresponding latent variables scores. To assess the quality of the whole measurement model by means of the average communality index is as follows

$$1 \quad \overline{com} = \sum P \quad \sum Pq com.$$

$$q: Pg > 1$$

$$q \quad q: Pg > 1$$

Redundancy index: It is a measure of how much of a block's variability is explained by its latent variables, and it is calculated for each endogenous block using a redundancy index that is derived for the j th endogenous endogenous latent variable. According to this example: $ed_j = com_j \times R^2(\Lambda^* \quad \Lambda^* \quad \Lambda^*)$.

$$y \quad q: \quad g \rightarrow j$$

Also, the average redundancy for the structural model is computed as follows:

$$J \quad \overline{red} = 1 \sum re,$$

$$J \quad j$$

where J is the total number of endogenous latent variables in the model.

Goodness of Fit index (GoF): The goodness of fit index was proposed by Tenenhaus et al in the year 2004. This index provides the model performance in the measurement model and structural model, thus provide

asinglemeasurefortheoverallpredictionperfor
manceofthemodel.Thegoodnessoffitindexiscal
culatedasthegeometricmeanoftheaveragecom
munalityindexandaveragecorrelationsquareeva
lueanditisdenotedasfollows:

$$GoF = \sqrt{(\overline{cm} + \overline{R^2}) / 2}$$

wheretheaveragecorrelationsquarevalueisobt
ainedasfollows:

$$R^2 =$$

$$1 - R^2 = \frac{\sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2}{\sum_{j=1}^J \sum_{q=1}^Q y_{jq}^2}$$

$$y_{jq} = \hat{y}_{jq} + (y_{jq} - \hat{y}_{jq})$$

$$J = \sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2$$

Thereforethegoodnessoffitindexisdefinedasint
hefollowingequation

$$Pg =$$

$$2 \times \sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2$$

$$\sum_{j=1}^J \sum_{q=1}^Q y_{jq}^2$$

$$R^2 = \left(\frac{\sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2}{\sum_{j=1}^J \sum_{q=1}^Q y_{jq}^2} \right)$$

$$(\sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2 / \sum_{j=1}^J \sum_{q=1}^Q y_{jq}^2)$$

$$(x_{pq} - \hat{x}_{pq})^2$$

Table3

Constructs	Cronbach's alpha	Dillon-Goldstein's rho	Eigenvalues
1 ξ^*	0.841	0.7363	2.560
2 ξ^*	0.790	0.785	2.392
3 ξ^*	0.817	0.804	1.962
4 ξ^*	0.972	0.799	3.081

6.1

According to the aforementioned Table 3, the
Cronbach's alpha values for the following
variables are as follows: 1 2 3 4 1 2 3 4 1 2 3 4
1 2 3 4 1 2 3 4 These numbers are higher than
the 0.7 threshold set by the standards. Dillion-

$$j=1$$

$$y_{jq} = \hat{y}_{jq} + (y_{jq} - \hat{y}_{jq})$$

$$GoF =$$

$$\sum_{j=1}^J \sum_{q=1}^Q (y_{jq} - \hat{y}_{jq})^2$$

$$q:Pg > 1q$$

6.

Application of PLS Nonlinear SEM for CardioVascular Disease

Two linear latent constructs, one interaction
construct, one latent quadratic construct, and
one endogenous construct are all used in the
theoretical model's construction. To estimate
the parameters, the partial least squares
nonlinear structural model is used, and the
following sections show how to do so using R
Language 3.5.1.

Measurement model assessment: The
unidimensionality, loadings, and
communalities are examined in this section.
When the linked indicators of a construct
increase or decrease in the same direction,
this is referred to as unidimensionality. The
amount of variance explained by a latent
variable is measured as the square of loading,
which is referred to as
communality. Unidimensionality

(DG) Goldstein's rho values are more than 0.7
if the block is regarded unidimensional. The
observed rho values are more than the
threshold value 0.7. Indicators that have Eigen
values greater than 1 are better at describing

the concept. More than one Eigen value was detected. The three indices, Croanbach alpha, Dillion-rho, Goldstein's and Eigen values, all meet the required norms for their respective categories. In other words, we might say that the indicators explain the construction of the model.

6.2 Loadings and Communalities

The loadings explain the correlation between a latent variable and its manifest variables, and the communalities are the square of correlations. The loadings and communalities are represented in the following Table 4

	Estimate	Std.Error	t value	Pvalue	Result
$\xi_1^* \rightarrow \xi_5^*$	-0.627	0.0730	8.5890	0.000	Significant***
$\xi_2^* \rightarrow \xi_5^*$	-0.503	0.0652	7.7147	0.000	Significant***
$\xi_3^* \rightarrow \xi_5^*$	-0.685	0.0512	13.3789	0.000	Significant***
$\xi_5^* \rightarrow \xi_5^*$	-0.561	0.0505	11.1089	0.000	Significant***

Table 4

Construct	Manifest variable	Weight	Loading	Communality
1 ξ^*	X ₁	0.8388	0.8857	0.7845
	X ₂	0.7289	0.7652	0.5855
	X ₃	0.7112	0.8546	0.7303
2 ξ^*	X ₄	0.8373	0.6974	0.4864
	X ₅	0.8895	0.8938	0.7989
	X ₆	0.7078	0.7183	0.5160
3 ξ^*	X ₇	0.7840	0.8737	0.7634
	X ₈	0.8457	0.7863	0.6183
	X ₉	0.7769	0.6806	0.4632
4 ξ^*	X ₁₀	0.7626	0.7741	0.5992
	X ₁₁	0.7935	0.7222	0.5216
	X ₁₂	0.7321	0.8284	0.6862

4	5				
$\xi_1^* \rightarrow \xi_6^*$	-0.751	0.0809	9.2750	0.000	Significant***
$\xi_2^* \rightarrow \xi_6^*$	-0.613	0.0676	9.0642	0.000	Significant***
$\xi_3^* \rightarrow \xi_6^*$	-0.780	-0.0727	10.7351	0.000	Significant***
$\xi_4^* \rightarrow \xi_6^*$	-0.549	0.0612	8.9726	0.000	Significant***
$\xi_5^* \rightarrow \xi_6^*$	0.773	0.0786	9.8364	0.000	Significant***

Table 4 shows the estimated weights based on the pls-pm algorithm. Linear latent variable () has provides the communalities for all of the aforementioned indicators.

weights ranging from 0.7112 to 0.8388; another linear latent variable () has weights ranging from 0.7078 to 0.8895; and an interaction variable () has weights ranging from 0.7769 to 2.3

Weights in the quadratic variable () range from 7112 to 8328, with an average of 0.8457. The manifest variables for its constructs are also given loading. The minimum loading is 0.6806, and the highest loading is 0.8938, which greatly explains its structure. ' Table 4

6.3 Structural Model Assessment

In this section, the determination of coefficients, the redundancy index and goodness of fit indices results are discussed. The statistical package R language version 3.5.1 is used and the derived outputs are given in the following Table 5

Table 5

significant at 1% level

Ejection Fraction () and () are endogenous latent constructs, and each construct's coefficient is significant at a 1% level toward each other. Linear latent variables have p values smaller than 0.01

which, even at a 1% level, is significant. The coefficient value of the latent variable () is found to have an impact on

Positively the Ejection Fraction () endogenous latent variable.

Endogenous latent variable () is adversely affected by latent variable () with a coefficient value of -0.503 and a p value of 1 percent. At a 1% significance level, the coefficients of interaction () and quadratic 5 3 effects () are significant. These factors have a detrimental impact on the Ejection Fraction (). Latent variables out of four:

4 5 interaction effect has a greater impact on the endogenous variable than the single factor does. The quadratic equations Second in line is first linear latent; third is effect; and fourth is second linear latent. These latent exogenous variables have p

values less than 0.01 which are significant at one percent significance.

1 2 3 4 5

The percentage point. Using these exogenous factors, it can be deduced that a latent endogenous variable is being affected. The next in line is the latent interaction construct, which exerts a significant influence on the endogenous variable.

3 6 is the author. is the most insignificant participant. The endogenous variable has a positive influence on the other variables.

1 4 5 is an internal determinant.

6.4 Model Testing

In this section, the communality index, redundancy index and goodness of fit index are explained in the following.

Communality Index: The Communality is calculated to check the manifest variables in a block which are explained by its latent construct. Communalities are the squared loadings of manifest variable in a construct. The communality of each block is represented in the following Table 6

Table 6

Construct	Type	Block Communalities	Mean Redundancy
1 ξ^*	Exogenous	0.7001	0.0000
2 ξ^*	Exogenous	0.6004	0.0000
3 ξ^*	Exogenous	0.6150	0.0000
4 ξ^*	Exogenous	0.6023	0.0000
5 ξ^*	Endogenous	0.0000	0.7360
6 ξ^*	Endogenous	0.0000	0.8925

Each construct's communality is obtained and given in Table 6. The communalities of ξ^* , ξ^* , ξ^* , ξ^* are 0.7001, 1 2 3 4

0.6004, 0.6150 and 0.6023 respectively. The block communalities are attained more than the minimum threshold value 0.5.

Redundancy Index: The tally sheet The independent latent variables connected with the endogenous latent variables predict a percentage of the variance of indicators in an endogenous block using redundancy. Because of the great degree of repetition, the external latent constructions can accurately predict the endogenous latent construct. Based on data in Table 6, we can deduce that the redundant value is 0.7360. Using exogenous latent constructs, it explains the degree of variability in the endogenous latent construct (ξ). Variability in ξ is responsible for 73.60% of the variance in the data. There is more redundant information in ξ than there is in ξ .

5 6 5

Goodness of fit Index: Measurement and structural models both benefit from the goodness of fit index, which measures how well they fit the data. The geometric mean of the average communality and the average R^2 value is used to determine the goodness-of-fit index. The specified model has a goodness of fit index of 0.837. The model's accuracy at predicting the future is 83.7 percent in this case. There is no criterion or threshold value for comparing the quality of fit in the goodness of fit. According to this one-rule, an estimated model may only be considered good if its goodness of fit increases.

Because of this, it can be stated that the partial least square nonlinear structural equation model is a method for estimating parameters and discovering the link between variables without making assumptions. A partial least square nonlinear structural equation model is found to be well-suited to explain the link between exogenous and endogenous latent constructs, as stated in the previous sections on communality and redundancy. In the linear and nonlinear estimations, the interaction effect accounts for more than the other components.

REFERENCE

- Cassel, C., Hackl, P., and Westlund, A. H. (1999). Robustness of partial least squares method for estimating latent variable quality structures. *Journal of Applied Statistics*, 26(4), 435-446.
- Cassel, C., Hackl, P., and Westlund, A. (2000). On measurement of intangible assets: a study of robustness of partial least squares. *Total Quality Management*, 11, 897-907.
- Chin, W. W. (1998). The partial least squares approach to structural equation modelling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-358). Mahwah, NJ: Lawrence Erlbaum.
- Fornell, C. G., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, 19, 440-452.

Lohmoller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Heidelberg, Germany: Physica.

Tenenhaus, M., Amato, S., & Esposito Vinzi, V. (2004). A global goodness-of-fit index for PLS structural equation modeling. In *Proceedings of the XLII Scientific Meeting* (pp. 739-742). Padova, Italy: CLEUP.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, 48, 159-205.

Wold, H. (1975). Path models with latent variables: The NIPALS approach. In H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon, & V. Capecchi (Eds.), *Quantitative sociology: International perspectives on mathematical and statistical modeling* (pp. 307-357). New York: Academic Press.

Wold, H. (1975a). PLS path models with latent variables: the NIPALS approach. In H. M. Blalock, A. Aganbegian, F. M. Borodkin, R. Boudon, and V. Capecchi (Eds.), *Quantitative sociology: international perspectives on mathematical and statistical modeling*. New York: Academic Press.

Wold, H. (1982). Soft modeling: The basic design and some extensions. In K. G. Joreskog & H. Wold (Eds.), *Systems under indirect observations: Part II* (pp. 1-54). Amsterdam: North-Holland.

Wold, H. (1985). Partial least squares. In S. Kotz & N. L. Johnson (Eds.), *Encyclopedia of statistical sciences* (pp. 581-591). New York: John Wiley.