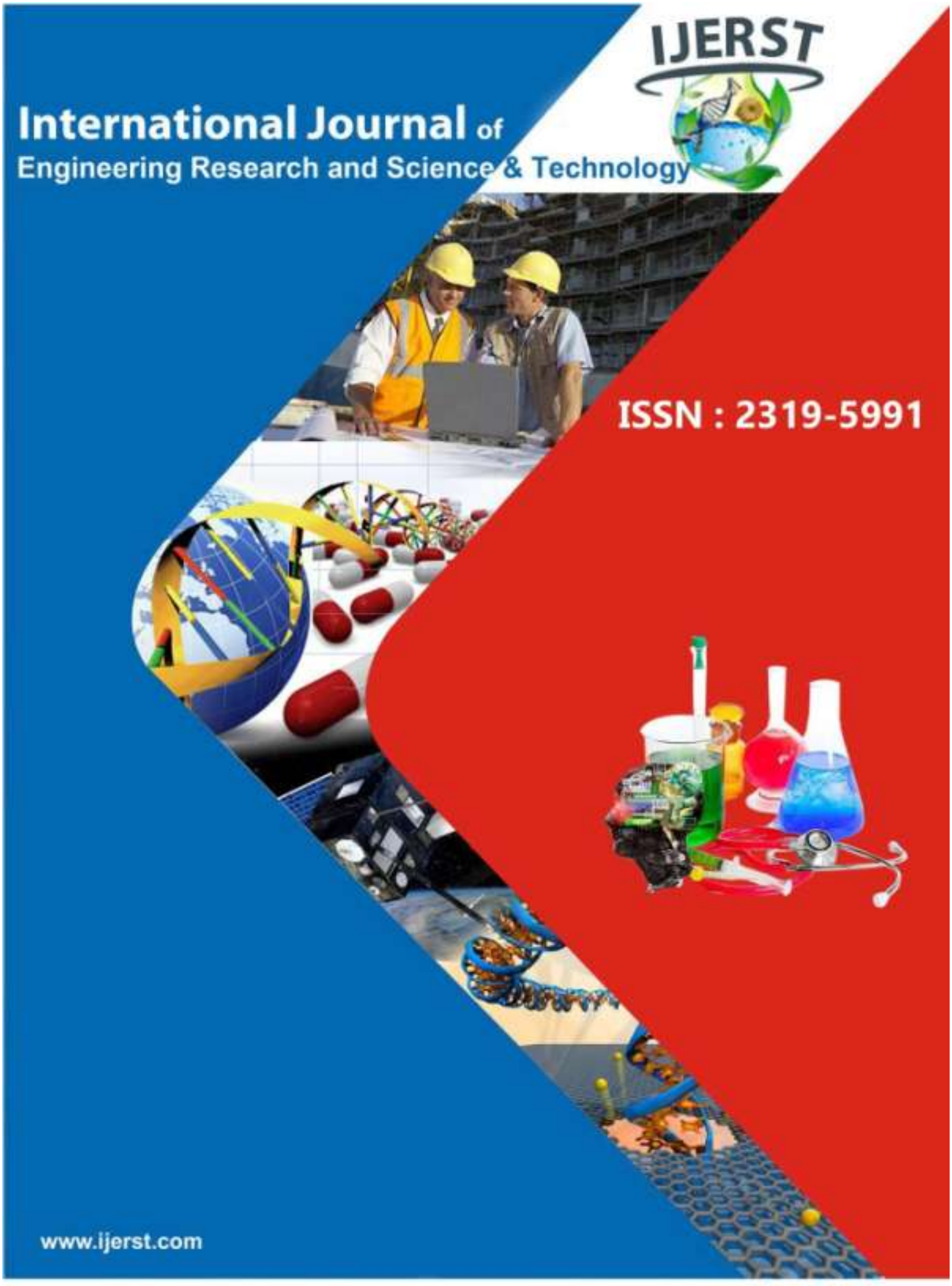

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Partial Least Square Non-Linear Structural Equation Modelling for Cardio Vascular Disease

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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.

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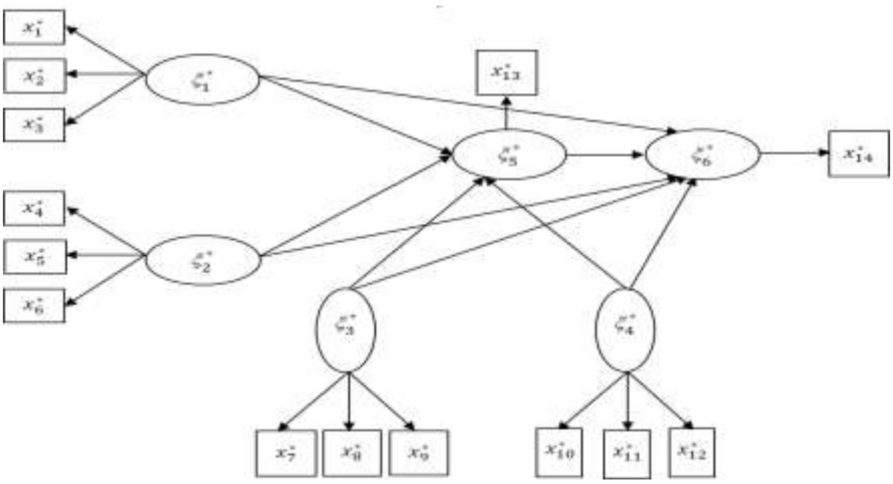
2. DATACHARACTERISTIC

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. ThePLS-SEMModelSpecification

Based on partial least square approach, we have considered two measurement models namely linear latentmeasurementmodelandnonlinearlatent measurementmodelwhichareexhibitedinDiagram1.



3.1 StructuralModel

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 56 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.Diagram1 APartialLeastSquareNonlinearstructuralequationmodelconsistslatentlinearcriterion?∗and?∗, alatent
1 2
interactionterm?∗andalatentquadraticterm?∗ andlatentendogenousvariables?∗and?∗
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.

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 Xpq (where Xpq is the pth variable in the qth block; q=1,2,3,..., 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 dij equals 1.

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

Table1

	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

Thestructuralequationmodellingforthespecifiedmodelisconstructedinthefollowingequation.
$Y=YB+ð$,
where Y is the matrix of latent exogenous and endogenous variables, B is the coefficient matrix and the error ðisassumedto becentred,that is$E$(ð)=0and$V$(ð)=1.

3.17 Themeasurementmodel

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 qth block has zero mean and is not linked with error pq. The following equation expresses the linear relationships in a standard regression perspective.(xpq/�∗)=�p0+�pq�∗ .

q q

Thisassumption,definedaspredictorspecification,assuresdesirableestimationpropertiesinclassicalOrdinaryLeastSquaresmodelling.

3.17.1 Reflectivemeasurement

Inthismeasurement,eachblockofmanifestvariablesreflectsit'slatentvariableandcanbewrittenasthemultivariateregression Xq=�∗wT+s

[|�∗]=0.

q q q,

So,wTcanbeestimatedbyleastsquaresas

q q

w^T=(�∗T�∗)−1�∗TX

q q q

q q

−1

=�∗TV(�∗ Co(�∗,X)

q q) q q

=Co(�∗,Xq)

=Co(�∗,Xq).

The partial least square algorithm estimates all the latent variables �∗, q=1,2,3,...,Q,as a linear combination oftheirmanifestvariablesundertheconstrainttohaveunitvariance.Weassumedallthemanifestvariablestobescaledtozeromeanandunitvariance.

3.17.2 Weightmatrix

Whenallthelatentvariablesinthemodelaremeasuredreflectively,itiscalledareflectivemodel.Letpq=

{p∈{1,2,3,...,P}|xp~�∗}beasetofindicesformanifestvariablesrelatedtolatentvariable�∗sothatw

q,q=

q q

1,2,3,...,Qisacolumnvectoroflength|pq|.TheouterweightsmatrixWcanbewrittenasfollows

W=| 0 0 w3 ... 0 |.

: : : ... 0

h0 0 0 0 wq

Table2representstheadjacencymatrixMforthemeasurementmodel.IthasthesamestructureasthematrixofouterweightsWasitisusedfortheinitialization.Iftheentry�pq=1thenmanifestvariable�$p$isoneoftheindicatorsofthelatentvariable�∗.

Table2

	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

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 BlockHomogeneityandunidimensionality

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. Thepartialleastsquarealgorithm

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

Stage1.

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 ofxpq is zero and the variance ofxpq 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� ^=𝑋𝑀

^∗

^∗ = g ,whereq=1,2,3,..,Q.

𝑞 √𝑣𝑎𝑟i(�^∗)

Thelatentvariablesareinitialized,sothatweget� ^=(� ,…,�).

1 Q

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

� ̃= �𝐵̂,

whereBisthematrixof innerweights,therefore� ̃ estimation� ^=(�∗,̃…,� ̃).

� ̃

= g ,whereq=1,2,3,..,Q.Weobtaintheinner

√𝑣𝑎𝑟i(� ̃)

1 Q

Stage3. 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 aregressor. Here's how it's explained:

w^𝑇=(� ̃𝑇̃∗

−1

X=𝑐𝑜𝑟(�𝑞,X𝑞).

Stage4.The blocksX1,X2,X3,…,XQarearranged inmatrixX,andthe outer weights vectorsw1,w2,w3,….,wQarearranged as outer weights matrix W. These matricesare used to estimate the factors scores by means of themanifestvariables

^

� ^=XWand�̂= g

,where� ^=(�∗,� ,…,�).

𝑞 √𝑣𝑎𝑟(�^)

1 2 Q

Stage5.Iftherelativechangeofalltheouterweightsfromoneiterationtothenextissmallerthenapredefinedtolerance

w^𝑝𝑞(o𝑙𝑑) − w^𝑝𝑞(𝑛ew)
|
w^𝑝𝑞(𝑛ew)

|<𝑡𝑜𝑙𝑒𝑟𝑎𝑘𝑐e

forall𝑘=1,2,3,…,𝐾𝑎𝑘𝑑𝑞=1,2,3,…,𝑄.Theconvergenceisattainedatthethresholdvalueortolerancevalue1.10−5.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 nodei that moves toward the arc's head, which is node j, for any dij = 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 () is expressed.� ˜=�𝐸^
Furthermore,letusdenote𝑅=𝑐𝑜𝑟(� ^),theempiricalcorrelationmatrixforthelatentvariablesresultingfrom theouterestimationand𝐶=𝐷+𝐷𝑇asymmetrical matrix.

Centroidweightingscheme:Followingthecentroidweightingscheme,thematrixof innerweights Etakestheform

eij

={𝑠𝑖𝑔𝑘(𝑟ij), fo𝑟𝑐ij=1}, i,j=1,2,3,…,𝑄.
0 , o𝑡ℎ𝑒𝑟wi𝑠e

Factorialweightingscheme:Thefactorialweightingscheme
={, =1},,=1,2,3,…,.
0 , ℎ

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

Pathweighting scheme:InIn 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 arch'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.
�∗=�∗𝑝𝛾+, [𝑧]=0, i=1,2,3,…,𝑄,
i i i i
with�∗(𝑝𝑟𝑒𝑑)thepredecessorsetofthelatentvariable�∗.Letbe�∗𝑠thesuccessorsetofthelatentvariable�∗

i
theelementoftheinnerweightmatrix𝐸are
𝛾

i i 𝑞

,fo𝑟jC�∗𝑝

j i
e = 𝑐o(�∗,�∗) , fo𝑟jC�∗𝑠
i i j i
0 ,o𝑡ℎ𝑒𝑟wi𝑠e.

Estimationofparameters:Oncethefactorscoresareestimatedbythepartialleastsquarealgorithm,thepathcoefficientstobe estimatedby usingthe ordinaryleastsquare method accordingto the structuralmodel.For

eachlatentvariable�^∗

,wℎ𝑒𝑟𝑒𝑞=1,2,3,…,𝑄,thepathcoefficientisthereg ressioncoefficientonits predecessorset□∗p

^ ^∗pT^∗

−1^∗pT^∗

βq=(□q

q)

q q

Weobtaintheelements$b$^ij,i,j=1,2,3,…,Qofthee stimated matrixofthepathcoefficients$B$^,

β^ij={

β^qj

, for$r$j∈ □∗p

0 , $otherwise$. Thematrix$B$^beinterpretedasatransitionmatrix for thestructuralmodel.

5. TheQuality 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: Foreachqthblockinthemodelwithmorethanone manifestvariable,thequalityofthemeasurementmodelisassessedbymeansofthecommunalityindex

Pg

1

co= ∑ $corr$2(x

,□^∗),fo$rallq$:

>1.

q Pq

p=1

pq q q

Communalityindexexplainshowmuchofthemanifestvariablesvariabilityintheqthblockbytheir ownlatent variablescores□^∗ .Thecommunalityintheqthblockisaverageof thesquaredcorrelationsbetweeneach manifestvariableandthecorrespondinglatentvariablescores.Toassessthequalityofthewholemeasurementmodelbymeansoftheaveragecommunalityindexisasfollows

1

$\bar{\bar{com}}$ =∑ P ∑$Pqcom$.

q:Pg>1

q 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 jth endogenous endogenous latent variable. According to this example:$e$$d$j= comj×R2(□ ,□ ∗ ∗).

y q:□ g→□ j

Also,theaverageredundancyforthestructuralmodeliscomputedasfollows:

J

$\bar{red}$=1∑re ,

J j

j=1

whereJisthetotalnumberofendogenouslatentvariablesinthemodel.

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

asinglemeasurefortheoverallpredictionperformanceofthemodel.Thegoodnessoffitindexiscalculatedasthegeometricmeanoftheaveragecommunalityindexandaveragecorrelationsquarevalueanditisdenotedasfollows:
$GoF=\sqrt{(\overline{com} \times \overline{R2})}$,
wheretheaveragecorrelationsquarevalueisobtainedasfollows:

$\overline{R2}$=

1R2(� ♠,� ♠

∗ ∗).

J y q:� g→� j

Thereforethegoodnessoffitindexisdefinedasinthefollowingequation

Pg

2 ^∗

∑J

R2((� ♠,� ♠ ∗ ∗))

(∑q:Pg>1 ∑p=1$corr$

(xpq,�q)

j=1

y q:� g→� j

GoF=

∑ P × J .

q:Pg>1q

6. ApplicationofPLSNonlinearSEMforCardioVascularDisease

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

Table3

Constructs	Cronbach’salpha	Dillon-Goldstein’srho	Eigenvalues
ξ^*_1	0.841	0.7363	2.560
ξ^*_2	0.790	0.785	2.392
ξ^*_3	0.817	0.804	1.962
ξ^*_4	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-(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 LoadingsandCommunalities

The loadings explain the correlationbetween a latent variable andits manifest variables,andthe communalitiesarethesquareofcorrelations.Theseloadingsandcommunalitiesarepresentedinthe followingTable4

Table4

	Estimate	Std.Error	|t|value	Pvalue	Result
$\xi^*_1 \to \xi^*_5$	-0.627	0.0730	8.5890	0.000	Significant***
$\xi^*_2 \to \xi^*_5$	-0.503	0.0652	7.7147	0.000	Significant***
$\xi^*_3 \to \xi^*_5$	-0.685	0.0512	13.3789	0.000	Significant***
$\xi^* \to \xi^*$	-0.561	0.0505	11.1089	0.000	Significant***

Construct	Manifestvariable	Weight	Loading	Communality
ξ^*_1	X_1	0.8388	0.8857	0.7845
	X_2	0.7289	0.7652	0.5855
	X_3	0.7112	0.8546	0.7303
ξ^*_2	X_4	0.8373	0.6974	0.4864
	X_5	0.8895	0.8938	0.7989
	X_6	0.7078	0.7183	0.5160
ξ^*_3	X_7	0.7840	0.8737	0.7634
	X_8	0.8457	0.7863	0.6183
	X_9	0.7769	0.6806	0.4632
ξ^*_4	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 aforementione d 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 StructuralModelAssessment

In this section, the determination of coefficients, the redundancy index and goodness of fit indices results arediscussed. The statistical package R language version 3.5.1is used and the derived outputsare given in thefollowingTable5

Table5

significantat1%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 5interaction 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 6is the author. is the most insignificant participant. The endogenous variable has a positive influence on the other variables.

1 4 5is an internal determinant.

6.4 ModelTesting

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

Communality Index: The Communality is calculated to check the manifest variables in a block which areexplained by its latent construct. Communalities are the squared loadings of manifest variable in a construct. Thecommunalityofeachblockisrepresentedint hefollowingTable6

Table6

Construct	Type	BlockCommunality	MeanRedundancy
ξ^*_1	Exogenous	0.7001	0.0000
ξ^*_2	Exogenous	0.6004	0.0000
ξ^*_3	Exogenous	0.6150	0.0000
ξ^*_4	Exogenous	0.6023	0.0000
ξ^*_5	Endogenous	0.0000	0.7360
ξ^*_6	Endogenous	0.0000	0.8925

EachconstructscommunalityisobtainedandgiveninTable6.Thecommunalitiesof ξ^*_1,ξ^*_2,ξ^*_3,ξ^*_4 are0.7001, 0.6004, 0.6150 and 0.6023 respectively. The block communalities are attained more than the minimum thresholdvalue0.5.

RedundancyIndex: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 (). Variability in is responsible for 73.60% of the variance in the data. There is more redundant information in than there is in .
5 6 5

GoodnessoffitIndex: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 R2 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.

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