



## Partial Least Squares Structural Equation Modelling To Determine The Effect Of Some Selected Factors On Business Performance

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### Abstract

Partial Least Squares Structural Equation Modeling (PLS-SEM) has gained popularity as a method for estimating (complex) path models with latent variables and their relationships. In a research study conducted in Abuja, SmartPLS 4 software was used to investigate the effects of selected factors on business performance and growth in four major markets: Garki Market, Wuse Market, Deidei Market, and Kado Fish Market. The study involved business owners engaged in retail, supplies, distribution, or wholesale in these markets. Questionnaires on factors affecting business performance and growth were distributed among the business owners, and their responses provided demographic data and information on latent variables. The analysis revealed that individuals, family, business environment, financial institutions, and government significantly influence the business performance and growth of business owners.

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### 1. Introduction

The use of partial least squares (PLS) as an alternative to factor-based structural equation modeling (SEM) has been increasing in various fields (Hair et al., 2022, Jöreskog & Wold, 1982). PLS-SEM applications have grown significantly, especially in social sciences (e.g., Ali et al., 2018; Ringle et al., 2020; Willaby et al., 2015), and other scientific disciplines such as agricultural science, engineering, environmental science, and medicine. This growth can be attributed to user-friendly software, guideline articles, and textbooks that make the method accessible to non-technical users.

Hair et al. (2012) paper has received a significant number of citations, indicating its lasting influence on marketing and consumer behavior. The researchers examined over 200 PLS SEM studies published in the top 30 marketing publications between 1981 and 2010. In their evaluation, Hair et al. (2012, p. 428) assessed PLS-SEM applications based on various factors such as model properties and assessment procedures. The authors draw attention to misapplications of the technique, even in top-tier marketing journals. They point out that researchers sometimes misapply measures and do not fully capitalize on the criteria available for model assessment. The authors also provide comprehensive recommendations for algorithmic settings, measurement, and structural model assessment criteria, as well as supplementary studies. These guidelines serve as a foundation for the method's subsequent developments and applications. Since then, there have been numerous methodological advancements in the PLS-SEM sector (Hwang et al., 2020; Khan et al., 2019). Research has contributed to a better understanding of the approach (e.g., Rigdon, 2012), introduced new measures (e.g., Liengaard et al., 2021), and addressed

model formulation and data concerns (e.g., Sarstedt et al., 2016). These developments are important for users of PLS-SEM. In recent years, there have been several developments in the area of PLS-SEM. Some of these developments include guidelines for diagnosing and treating endogeneity (Bendler & Huang, 2014; Dijkstra & Henseler, 2015; Kock, 2019) and new techniques for evaluating discriminant validity (Henseler et al., 2015), which emerged from debates about the overall effectiveness of PLS-SEM (Evermann & Rönkkö, 2021). Additionally, best practices in PLS-SEM have become more established, particularly in the areas of measurement and structural model assessment (Hair et al., 2020b). But is the use of PLS-SEM in marketing research understood and accepted? Have researchers included the most recent recommendations for best practices? Are misapplications occurring as previously noted by Hair et al. (2012)

To understand the relationship between data, measurement, and model estimation in Partial Least Square Structure Equation Modelling (PLS-SEM), it's important to grasp three key points. First, in PLS-SEM, all indicators of formative measurement models are treated as composite indicators. Therefore, a formatively specified construct in PLS-SEM does not have an error term, unlike causal indicators in factor-based SEM (Diamantopoulos 2011). When using partial least squares structural equation modeling (PLS-SEM) with data from a common factor model population, the parameter estimates may deviate from the specified values. In this case, the measurement model parameters are often overestimated and the structural model parameters are underestimated, leading to what is known as PLS-SEM bias. This issue tends to diminish as the sample size and the number of indicators per concept increase, a phenomenon referred to as consistency at large. However, because the characteristic is based on specific assumptions about the nature of the data that may or may not be valid, recent research on Partial Least Square Structural Equation Modeling (PLS-SEM) suggests that researchers should avoid using the term "PLS-SEM bias" (e.g., Rigdon 2016). Specifically, estimations in Partial Least Square Structural Equation Modeling (PLS-SEM) are unbiased and consistent when the data is derived from a composite model population where linear combinations of the indicators define the data's nature (Sarstedt et al. 2016b). It has been shown in studies that when estimating data from common factor model populations, Partial Least Squares Structural Equation Modelling (PLS-SEM) tends to produce lower absolute bias compared to common factor-based SEM, particularly when estimating data from composite model populations (Reinartz et al., 2009; Sarstedt et al., 2016b). Also PLS-SEM uses composites, impacting both the method's measurement philosophy and its application. Unlike factor-based SEM, PLS-SEM always produces a specific score for each case per construct once the weights are derived. This sets it apart as factor-based SEM produces indeterminate construct scores, which can affect result validity (Rigdon et al. 2019). Using these specific scores as input, PLS-SEM applies a series of ordinary least squares regressions to estimate model parameters, maximizing the explained variance of endogenous constructs ( $R^2$  values). While this process enhances explanatory power, PLS-SEM is well-suited for prediction due to the computation of specific construct scores, allowing model parameters from a training sample to be applied to generate testable predictions for other observations (hold-out cases) not used in the model estimation (Hwang et al 2020). Several studies have shown evidence of PLS-SEM's effectiveness for prediction (Becker et al 2013a; Evermann and Tate 2016; Cho et al 2021). Through PLS-SEM, researchers gain an understanding of causal relationships based on theory and logic (explanation) as well as the model's predictive power, essential for establishing its practical relevance.

This study aimed to determine the use of latent variable scores and factor based SEM results of common factor models by using PLS (e.g when the model and/or data do not meet the requirements of factor-based SEM).

## **2. Methodology**

For this study, data was obtained from a primary source. A total of 392 questionnaires were distributed among selected individuals from Wuse, Deidei, Kado, and Garki Markets in Abuja, FCT. The aim was to gather information from business owners, as they are considered major stakeholders in business growth and standards in the state. The questionnaire focused on gathering information about the Factors Affecting Business Growth in Abuja Markets. It consisted of two sections: section A gathered information on the demographic profiles of respondents, while section B obtained information on factors influencing business growth, such as individual training in business, functional skills, experience in the business area, adaptability to the environment, drive, ambition, family influence on business growth, business environment, financial institutions, and government influence.

## **3. Research Design**

The following equation formally illustrates the relationship between a latent variable and its observed indicators:

$$d = \lambda p + e \quad (1)$$

Where:  $d$  is the observed indicator variable  $Y$  is the latent variable  $\lambda$  is the loading, which is a regression coefficient quantifying the strength of the relationship between  $d$  and  $p$ , and  $e$  represents the random measurement error  
A measurement model with causal indicators can be formally described as follows:

$$p = \sum_{k=1}^k w_k \cdot d_k + z \quad (2)$$

Where  $w_k$  indicates the contribution of  $d_k$  ( $k = 1, \dots, K$ ) to  $p$ , and  $z$  is an error term associated with  $p$ .

In formative measurement models with composite indicators, the error term, which in causal indicator models represents “omitted causes,” is set to zero in formative measurement models with composite indicators. A measurement model with composite indicators takes the following form, where  $p$  is a linear combination of indicators  $d_k$  ( $k = 1, \dots, K$ ), each weighted by an indicator weight  $w_k$  (Bollen 2011):

$$p = \sum_{k=1}^k w_k \cdot d_k \quad (3)$$

According to Henseler (2017, p. 180), measurement models with composite indicators “are a prescription of how the ingredients should be arranged to form a new entity,” which he refers to as artifacts. That is, composite indicators define the construct’s empirical meaning.

#### *Population and Sample Size*

Yamane simplified formula for proportion was used to calculate the sample size, using 0.05 as level of precision.

$$n = \frac{N}{1 + N(e)^2} \quad (4)$$

Where  $n$  = sample size,  $N$  = Population size and  $e$  = Level of precision

We utilize the Yamane simplified formula as it is frequently employed in survey research to determine the necessary sample size, particularly when dealing with a relatively large population.

#### **4. Estimation of Model**

A three-stage method from the family of (alternating) least squares algorithms is utilized for model estimation in Partial Least Square Structure Equation Modeling (PLS-SEM) (Mateos-Aparicio, 2011). The PLS-SEM algorithm, as described by Lohmöller (1989), is illustrated in the following step.

##### *Initialization*

Stage 1: Iterative estimation of weight and latent variable scores

Starting at step 1d, repeat steps 1a to 1d until convergence is obtained.

1a Inner weight (here obtained by using the factor weighting

$$r_{ij} = \begin{cases} \text{cov}(p_j; p_i) & \text{If } p_j \text{ and } p_i \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

1b Inside approximation

$$\hat{P}_j = \sum_t c_{ji} P_i \quad (6)$$

1c Outer weights; solve for

$$\begin{aligned} \hat{P}_{jn} &= \sum_{kj} \hat{w}_{kj} d_{kjn} + d_{jn} && \text{in a mode A block} \\ d_{kjn} &= \hat{w}_{kj} \hat{P}_{jn} + e_{kjn} && \text{in a Mode B block} \end{aligned}$$

1d Outside approximation

$$P_{jn} = \sum_{kj} \hat{w}_{kj} d_{kjn} \quad (7)$$

Stage 2: Estimation of outer weights, outer loadings, and path coefficients

Stage 3: Estimation of location parameters.

The algorithm begins with an initialization stage, during which it establishes preliminary latent variable scores. To compute these scores, the algorithm typically uses unit weights (i.e., 1) for all indicators in the measurement models (Hair et al. 2017b). Stage 1 of the Partial Least Square Structural Equation Modelling (PLS-SEM) algorithm iteratively determines the inner weights and latent variable scores using a four-step procedure, consistent with the algorithm’s original presentation

(Lohmöller1989). Inner weights refer to path coefficients, while outer weights and outer loadings refer to indicator weights and loadings in the measurement models. Step #1 uses the initial latent variable scores from the initialization of the algorithm to determine the inner weights between the adjacent latent variables (i.e., the dependent one) and (i.e., the independent one) in the structural model. The literature suggests three approaches to determining the inner weights ( Lohmöller 1989; Chin 1998; Tenenhaus et al. 2005). In the centroid scheme, the inner weight is set to +1 if the covariance between and is positive and -1 if this covariance is negative. If two latent variables are unconnected, the weight is set to 0. In the factor weighting scheme, the inner weight reflects the covariance between variables and is set to zero if the latent variables are not connected. On the other hand, the path weighting scheme considers the direction of the inner model relationships (Lohmöller 1989). Chin (1998, p. 309) explains that the path weighting scheme aims to create a component that can be ideally predicted and, at the same time, act as a good predictor for subsequent dependent variables. Consequently, the path weighting scheme tends to result in slightly higher values in the endogenous latent variables compared to the other schemes and is generally preferred. However, in most cases, the choice of the inner weighting scheme has minimal impact on the results (Noonan and Wold 1982; Lohmöller1989). In Step #2, the inner approximation involves calculating proxies for all latent variables by using the weighted sum of their adjacent latent variable scores. Then, in Step #3, new outer weights representing the strength of the relationship between each latent variable and its corresponding indicators are computed for all the indicators in the measurement models. The Partial Least Square Structure Equation Modelling (PLS-SEM) algorithm uses two different estimation modes for this purpose. When using Mode A (i.e., correlation weights), the outer weights are determined based on the bivariate correlation between each indicator and the construct. In contrast, Mode B (i.e., regression weights) computes indicator weights by regressing each construct on its associated indicators.

The estimation of reflectively specified constructs typically uses Mode A, while Partial Least Square Structure Equation Modeling (PLS-SEM) utilizes Mode B for formatively specified constructs. However, Becker et al. (2013a) demonstrated that this reflexive use of Mode A and Mode B is not always ideal. For instance, when constructs are specified formatively, Mode A estimation produces better out-of-sample prediction under specific conditions: when the model estimation involves more than 100 observations and when the endogenous construct's R<sup>2</sup> value is 0.30 or higher. The algorithm above provides the formal representation of these two modes with the respective symbols and steps. The PLS-SEM algorithm takes standardized data as input and always standardizes the generated latent variable scores in Step #2 and Step #4. The algorithm terminates when the weights obtained from Step #3 change marginally from one iteration to the next (typically 1×), or when the maximum number of iterations (typically 300) is reached (Henseler, 2010).

Stages 2 and 3 use the final latent variable scores from Stage 1 as input for a series of ordinary least squares regressions. These regressions produce the final outer loadings, outer weights, and path coefficients as well as related elements such as indirect and total effects, values of the endogenous latent variables, and the indicator and latent variable correlations (Lohmöller 1989).

### **5. Test of Reliability Using Cronbach's Alpha**

The Cronbach's alpha coefficient is a statistical tool used to assess the internal consistency or reliability of a set of test items or a scale. It measures the extent of interrelatedness among the items in the set. In other words, it indicates how well a measurement represents a concept consistently, and one way to measure this consistency is by examining its Cronbach's alpha value. Cronbach's alpha is computed by comparing the variance for all individual item scores to the correlation between the score for each item and the overall score for each observation (usually individual test takers or survey respondents).

$$t = \left( \frac{r}{r-1} \right) \left( 1 - \frac{\sum_{i=0}^r \sigma_{yi}^2}{\sigma_x^2} \right) \quad (8)$$

Where  $r$  refers to the number of scale items,  $\sigma_{yi}^2$  Item  $i$  variance refers to the variability associated with that specific item, and  $\sigma_x^2$  refers to the variance associated with the observed total score.

Cronbach's alpha measures the reliability of a test by considering the number of items in the test, the average covariance between pairs of items, and the variance of the total score. The resulting coefficient of reliability ranges from 0 to 1, providing an overall assessment of the measure's reliability. If all the scale items are completely independent (i.e., not correlated or sharing any covariance), then  $\alpha = 0$ . On the other hand, if all items have high covariances, then  $\alpha$  will approach 1 as the number of items in the scale approaches infinity.

## 6.Data Presentation and Results

### Data Presentation

Table 1 : Dei-Dei: Group of Markets

NAMES OF MARKETS	NO. OF SHOPS
BUILDING MATERIALS MARKET	3,066
TOMATO MARKET	807
REGIONAL MARKET	8,668
TIMBER (CARPARK)	1,489
LORRY PARK/CORNER SHOP	671
BUFFER ZONE	66 (CANOPY RESTAURANTS) 12 (GP TANKS RENT SPACES)
PANTAKER	72

Table2 : Kado Fish Market

OPEN STALLS	86
LOCK UP SHOP	257
WAREHOUSE	26
TOTAL	369

Table 3: Wuse Market

FORMAL SHOPS	1,592
WET INFORMAL	500
DRY INFORMAL	197
HAIR DRESSER	232
SITOUT	6
TOTAL	2,527

Table 4: Garki Market

FORMAL SHOPS	1255
PLAZA	367
OLD INFORMAL	125
INFORMAL SHOPS	1625
TOTAL	3,723

Source: Abuja Market Management, 2024

Table6 : 5 Major Markets

Market	No. of Shops	Proportion
Dei-Dei Market	3,066	153
Kado Fish Market	369	19
Wuse Market	2,527	127
Garki Market	1,625	81
Total	7,587	380

Source: Abuja Market Management

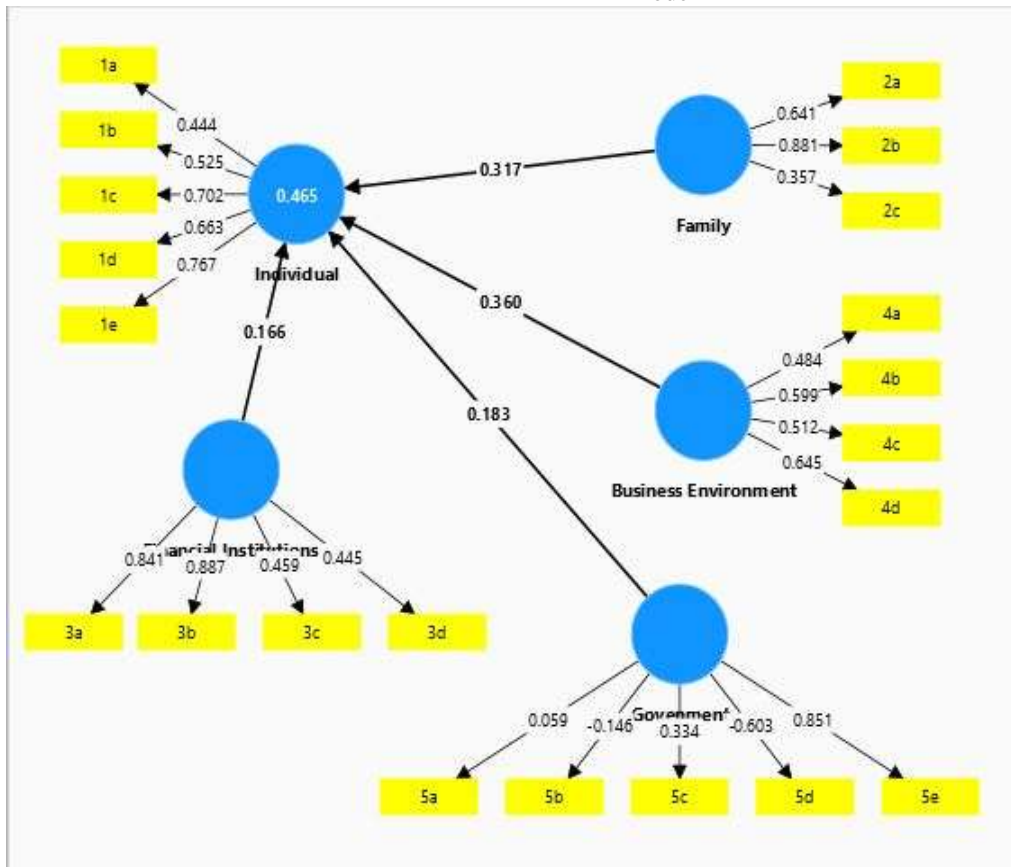
$$\text{Sample size } n = \frac{7,587}{1+7,587(0.05)^2} = 380$$

Yamane simplified formula for proportion tells us the sample size needed for a given population when conducting research, particularly when estimating the proportion of a certain characteristic or attribute within the population. So the sample size needed is 380 for the research work

Table 6: Demographic information of respondents

S/N	Items	Frequency	Percentage
Gender	Male	265	70
	Female	115	30
	Total	380	100
Years in business	1-5	52	14
	6-10	91	24
	11-15	105	27
	16-20	75	20
	21-25	22	6
	26-30	15	4
	31-Above	20	5
	Total	380	100
Business Location	Garki market	81	21
	Wuse Market	127	34
	Deidei Market	153	40
	Kado Fish Market	19	5
	Total	380	100
Business Type	Supplier	94	25
	Distributor	19	5
	Wholesaler	92	24
	Retailer	175	46
	Total	380	100

Model 1



Effects of individual, family, business environment, financial institutions, and government on the business performance of individuals.

Table 7: Path Coefficients/Total Effects

	Business Environm	Family	Financial Institut	Government	Individual
Business Environment					0.360
Family					0.317
Financial Institutions					0.166
Govenment					0.183
Individual					

Indirect effects :The model does not contain indirect effects.

Table 8: Outer Loadings

	Business Environm	Family	Financial Institut	Government	Individual
1a					0.444
1b					0.525
1c					0.702
1d					0.663
1e					0.767
2a		0.641			
2b		0.881			
2c		0.357			
3a			0.841		
3b			0.887		
3c			0.459		
3d			0.445		
4a	0.484				
4b	0.599				
4c	0.512				
4d	0.645				
5a				0.059	
5b				-0.146	
5c				0.334	
5d				-0.603	
5e				0.851	

## 7. Quality Criteria

Table : *R Square*

	R-square	R-square adjusted
ndividual	.465	.459

46.5% represents the percentage of variance in the dependent variable explained by the independent variables in the model. It measures how well the independent variables predict or explain the variation in the dependent variable.

Table 10: *f Square*

	Business Environn	Family	Financial Institut	Government	Individual
Business Environment					0.221
Family					0.150
Financial Institutions					0.039
Government					0.057
Individual					

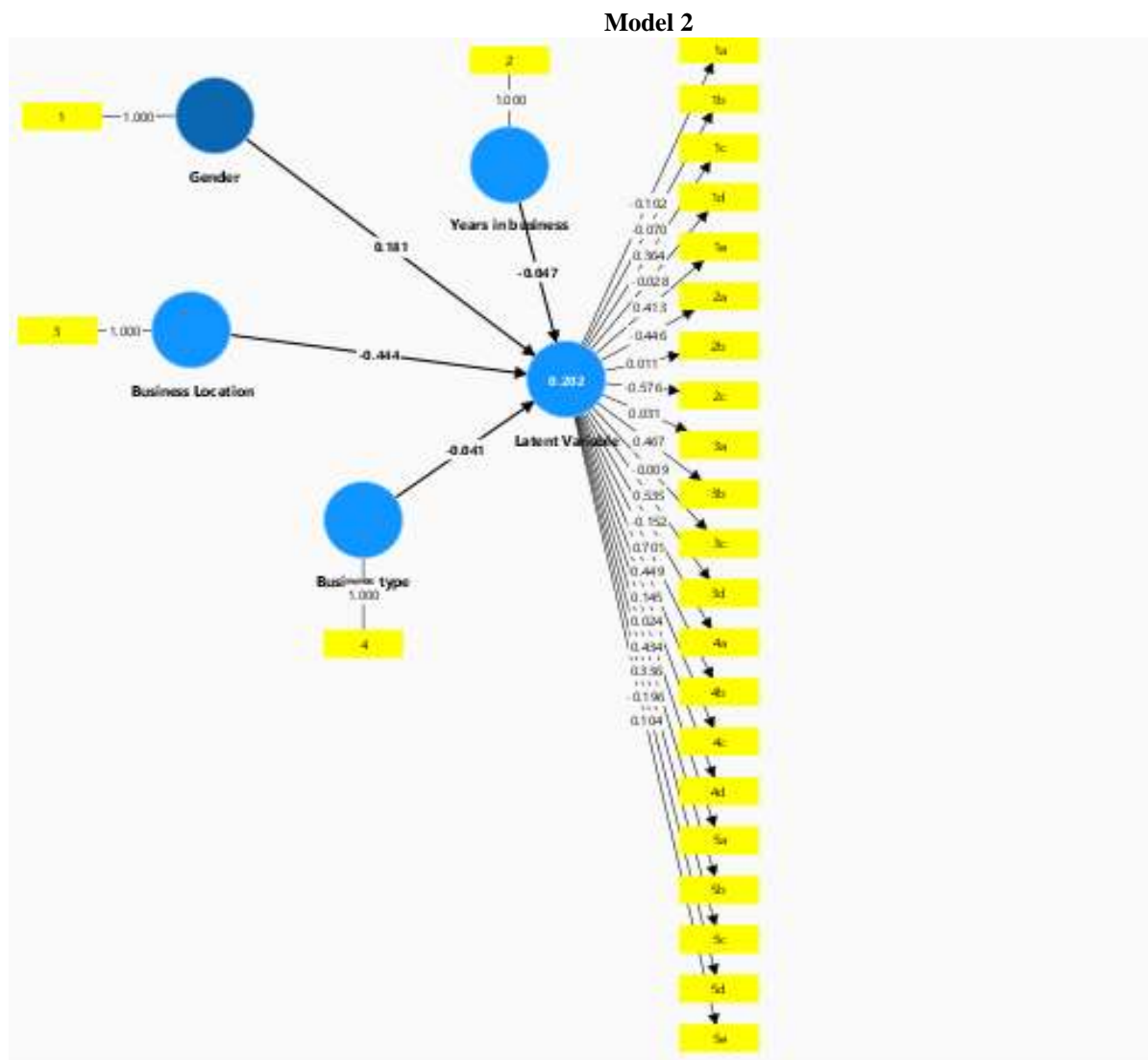
The effect size values indicated by *f square* of 0.02, 0.15, and 0.35 represent small, medium, and large effects (as per Cohen, 1988) of an exogenous latent variable, respectively. Effect size values below 0.02 indicate no effect. Table 11 illustrates that the business environment, family, financial institutions, and government all have an impact on the market.

Table 11: Construct Reliability and Validity

	Cronbach's alp	Composite reliability (rho_c)	Composite reliab (rho_c)	Average variance extrac (AVE)
Business Environment	0.301	0.290	0.648	0.318
Family	0.433	0.557	0.677	0.438
Financial Institutions	0.641	0.804	0.767	0.475
Government	0.080	0.308	0.061	0.245
Individual	0.649	0.669	0.762	0.399

In Model 1, a path analysis was conducted using Smart PLS. The formative model comprises individuals as it is an endogenous variable, with no intervening variable present. Consequently, there is no indirect effect on variables, and the total effect (path coefficient) is equal to the direct effect. This model aims to elucidate the impact of family, business environment, financial institution, and government on the growth and performance of individual businesses in four major markets in Abuja. The numbers on the path relationships represent the standardized regression coefficients, while the numbers within the circles of the endogenous latent variables indicate their values. Upon assessment, it was found that the business environment exerts the strongest influence (0.360) on business growth and performance, followed by family influence (0.317), government influence (0.183), and financial institution influence (0.166), which has the least effect on individual business performance and growth. Collectively, these four constructs account for 46% of the variance in the endogenous construct, Individual. The reflective measurement model entails assessment of the individual, family, government, and financial institution with indicators 1, 2, 3, 4 and 5, known as outer loadings. These represent the absolute contribution of the indicator to the definition of the latent variable. Generally, higher loadings indicate a stronger and more reliable measurement model. The reflective measurement model meets the relevant assessment criteria as the indicators display a sufficient level of reliability (>0.50). However, some indicators exhibit weak reliability, indicating minimal contribution to the variable. For individuals, indicator 1a (0.444) shows the least contribution, followed by 1b (0.525), 1d (0.663), 1c (0.702), and 1e (0.767) with the highest effect rate. In the Business Environment, 4a (0.484) has the least effect, followed by 4c (0.512), 4b (0.599), and 4d (0.645) showing stronger effects. Indicators 3d (0.445) have a weaker effect on the financial institution, while 3c (0.459), 3a (0.841), and 3b (0.887) have the strongest effect on financial institutions. The reflective measurement model entails assessment of the individual, family, government, and financial institution with indicators 1, 2, 3, 4 and 5, known as outer loadings. These represent the absolute contribution of the indicator to the definition of the latent variable. Generally, higher loadings indicate a stronger and more reliable measurement model. The reflective measurement model meets the relevant assessment criteria as the indicators display a sufficient level of reliability (>0.50). However, some indicators exhibit weak reliability, indicating minimal contribution to the variable. For individuals, indicator 1a (0.444) shows the least contribution, followed by 1b (0.525), 1d (0.663), 1c (0.702), and 1e (0.767) with the highest effect rate. In the Business Environment, 4a (0.484) has the least effect, followed by 4c (0.512), 4b (0.599), and 4d (0.645) showing stronger effects. Indicators 3d (0.445) have a weaker effect on the financial institution, while 3c (0.459), 3a (0.841), and 3b (0.887) have the strongest effect on financial institutions.





The relationship between demographic factors of respondents and individual perspectives on factors influencing business performance

*Table12:Path Coefficients/Total Effects*

	Business Loca	Business ty	Gender	Latent Varia	Years in busin
Business Location				-0.444	
Business type				-0.041	
Gender				0.181	
Latent Variable					
Years in business				-0.047	

*Table 13: Indirect Effects: Model does not contain Indirect Effects. Outer Loadings*

	Business Location	Business type	Gender	Latent Variable	Years in business
1			1.000		
1a				-0.102	
1b				-0.070	
1c				0.364	
1d				-0.028	
1e				0.413	
2					1.000
2a				-0.446	
2b				0.011	
2c				-0.576	
3	1.000				
3a				0.031	
3b				0.467	
3c				-0.009	
3d				0.535	
4		1.000			
4a				-0.152	
4b				0.701	
4c				0.449	
4d				0.145	
5a				0.024	
5b				0.434	
5c				0.336	
5d				-0.196	
5e				0.104	

*Table 14: Quality Criteria R Square*

	R-square	R-square adjusted
Latent Variable	0.202	0.194

*Table 15: f Square*

	Business Location	Business type	Gender	Latent Variable	Years in business
Business Location				0.210	
Business type				0.002	
Gender				0.008	
Latent Variable					
Years in business				0.002	

Table 16: Construct Reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Latent Variable	0.673	0.643	0.242	0.116

In Model 2, a path analysis is displayed using SmartPLS. The formative model (Latent Variable 1) includes all the different factors that affect business performance and the growth of individuals, as it is the endogenous variable. There are no intervening variables in this model, so there are no indirect effects on the variables. This means that the total effect (path coefficient) and the direct effect are the same. The purpose of this model is to explain how demographic factors impact the way business owners respond to business growth and performance.

The numbers along the paths represent the standardized regression coefficients, while the numbers within the circles of the endogenous latent variables represent their values. An evaluation reveals that Business location (-0.444) has the least negative impact on Latent Variable 1, followed by years in business (-0.047), Business type (-0.041), and Gender (0.181), which has the highest effect among business owners. These four factors collectively account for 20.2% of the variance in the endogenous construct Latent Variable.

An evaluation of the reflective measurement model (i.e., Latent Variable1) with indicators 1a, 1b, 1c, 1d, 1e, 2a, 2b, 2c, 3a, 3b, 3c, 3d, 4a, 4b, 4c, 4d, 5a, 5b, 5c, 5d, 5e, also referred to as outer loadings, represents the absolute contribution of the indicator to the definition of the latent variable. Generally, higher loadings indicate a stronger and more reliable measurement model. We observed that the reflective measurement model does not meet the relevant assessment criteria, as the outer loadings are below 0.70, except for 4b (0.701). This suggests that the indicators do not exhibit a sufficient level of reliability (i.e., <0.50). Some indicators do show a sufficient level of reliability, indicating their impact on the variable. Latent Variable1 is least affected by 2c (0.576), followed by 5d (0.196), 3d (0.535), and 4b (0.701), which has the highest effect on Latent Variable1. Beyond the reliabilities, the model is good and accurate. These results suggest that the construct measures the demographic factors Gender, Years in business, Business Location, and Business type, but do not exhibit sufficient levels of internal consistency reliability.

## 8. Summary and Conclusion

In model 1, the responses from individuals regarding business performance and growth indicated that all factors directly impacted the business performance and growth of business owners. The factor with the highest effect rate based on their responses was family (0.360), while the role of financial institutions had the least effect (0.166) on businesses. When considering the role of the individual as a factor, it was found that the individual's drive and ambition (1e- 0.767) had the greatest effect on business performance. This was followed by the individual's functional skills in sales and management (1c- 0.702), the individual's ability to adapt in such an environment (1d- 0.663), the individual's lack of experience in the business area (1b- 0.525), and the individual's lack of training in business (1a- 0.444), which had the least effect on business performance. Regarding the role of family as a factor, family influence and business support (2b- 0.881) made the strongest contribution to business performance, followed by family history and background in business (2a- 0.641), and family choice and expectations (2c- 0.357), which had the least contribution. For the role of financial institutions as a factor, the availability of financial support e.g. loans (3b- 0.887) had a stronger effect on business performance, followed by the turnaround time for business transactions (3a- 0.841), the policies of the Central Bank of Nigeria (3c- 0.459), and the quality of e-banking services e.g. POS, credit card, etc (3d- 0.445). In considering the role of the business environment as a factor, .payment of rent, service charge, dues, levies, etc. (4d- 0.645) made the highest contribution, followed by the location of the business (4b- 0.599), insufficient profits (4c- 0.512), and high and low demand for goods (4a- 0.484).

In model 2, the responses from individuals indicate that demographic factors such as gender, years in business, business location, and business type directly impact business owners' responses. Business location, years in business, and business type have a negative effect (0.444, 0.047, and 0.041, respectively) on individuals' responses, while gender (0.181) has the highest positive effect. The factors contributing to business performance, from highest to lowest, are as follows: location of business (4b- 0.701), quality of e-banking services (3d- 0.535), availability of financial support (3b- 0.467), insufficient profits (4c- 0.449), poor infrastructures and security (5b- 0.434), individual's drive and ambition (1e- 0.413), individual's functional skills in management and sales (1c- 0.364), lack of financial support from government (5c- 0.336), payment of rent, service charge, dues, levies, etc. (4d- 0.145), lack of effective monitoring by agencies (5e- 0.104), turnaround time for business transactions

(3a- 0.031), government policies (5a- 0.024), family influence and support in business (2b- 0.011), policies of the Central Bank of Nigeria (3c -0.009), individual's ability to adapt to the environment (1d -0.028), lack of experience in business areas (1b -0.070), lack of training in business (1a -0.102), high and low demand for goods (4a -0.152), bribery and corruption (5d -0.196), family history and background in business (2a -0.446), and finally, family choice and expectation (2c -0.576), which has the least impact on business performance.

## References

1. Ali, F., Rasoolmanesh, S. M., Sarstedt, M., Ringle, C. M., & Ryu, K. (2017). An assessment of the use of partial least squares structural equation modeling (Partial Least Squares Structural Equation Modelling (PLS-SEM)) in hospitality research. *International Journal of Contemporary Hospitality Management*, forthcoming.
2. Becker, J.-M., Rai, A., & Rigdon, E. E. (2013a). Predictive validity and formative measurement in structural equation modeling: Embracing practical relevance. In 2013 Proceedings of the International Conference on Information Systems, Milan.
3. Bentler, P. M., & Huang, W. (2014). On components, latent variables, PLS, and simple methods: Reactions to Rigdon's rethinking of PLS. *Long Range Planning*, 47(3), 138–145.
4. Bollen, K. A. (2011). Evaluating effect, composite, and causal indicators in structural equation models. *MIS Quarterly*, 35(2), 359–372. Bollen, K. A., & Bauldry, S. (2011). Three Cs in measurement models: Causal indicators, composite indicators, and covariates. *Psychological Methods*, 16(3), 265–284.
5. Cho, G., Hwang, H., Kim, S., Lee, J., Sarstedt, M., & Ringle, C. M. (2021). A comparative study of the predictive power of component-based approaches to structural equation modeling. Working Paper.
6. Dijkstra, T. K., & Henseler, J. (2015a). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, 81, 10–23.
7. Dijkstra, T. K., & Henseler, J. (2015b). Consistent partial least squares path modeling. *MIS Quarterly*, 39(2), 297–316.
8. Diamantopoulos, A. and Riefler, P. (2011), "Using formative measures in international marketing models: a cautionary tale using consumer animosity as an example", in Sarstedt, M., Schwaiger, M. and Taylor, C.R. (Eds), *Advances in International Marketing*, Emerald, Bradford, pp. 11-30.
9. Diamantopoulos A. (2011) Incorporating formative measures into covariance-based structural equation models. *Management Information Systems Quarterly*, 35, 335–358.
10. Dijkstra, T.K. and Hensler, J. (2014), "Consistent and asymptotically normal PLS estimators for linear structural equations", working paper, Economics and Business, University of Groningen, Groningen, June 17.
11. Dijkstra, T.K. and Schermelleh-Engel, K. (2014), "Consistent partial least squares for nonlinear structural equation models", *Psychometrika* (in press).
12. Elbanna, S., Child, J. and Dayan, M. (2013), "A model of antecedents and consequences of intuition in strategic decision-making: evidence from Egypt", *Long Range Planning*, Vol.46 Nos 1/2, pp. 149-176.
13. Esposito, V.V., Trinchera, L., Squillacciotti, S. and Tenenhaus, M. (2008), "REBUS-PLS: a response-based procedure for detecting unit segments in PLS path modeling", *Applied Stochastic Models in Business and Industry*, Vol. 24 No. 5, pp. 439-458.
14. Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators. *Journal of Business Research*, 69(10), 4565–4582.
15. Fornell, C.G. and Bookstein, F.L. (1982), "Two structural equation models: LISREL and PLS applied to consumer exit-voice theory", *Journal of Marketing Research*, Vol. 19 No. 4, pp. 440-452.

16. Fornell, C.G. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.
17. Gudergan, S.P., Ringle, C.M., Wende, S. and Will, A. (2008), "Confirmatory tetrad analysis in PLS path modeling", *Journal of Business Research*, Vol. 61 No. 12, pp. 1238-1249.
18. Hair, J. F., Sarstedt, M., Pieper, T. M., & Ringle, C. M. (2012a). The use of partial least squares structural equation modeling in strategic management research: A review of past practices and recommendations for future applications. *Long Range Planning*, 45(5-6), 320–340.
19. Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012b). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40(3), 414–433.
20. Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, 109, 101–110.
21. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Thousand Oaks: Sage.
22. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.
23. Henseler, J. (2017). Bridging design and behavioral research with variance-based structural equation modeling. *Journal of Advertising*, 46(1), 178–192.
24. Hwang, H., Sarstedt, M., Cheah, J.-H., & Ringle, C. M. (2020). A concept analysis of methodological research on composite-based structural equation modeling: Bridging PLSPM and GSCA. *Behaviormetrika*, 47(1), 219–241.
25. Jöreskog, K. G., & Wold, H. (1982). The ML and PLS techniques for modeling with latent variables: Historical and comparative aspects. In H. Wold & K. G. Jöreskog (Eds.), *Systems under indirect observation, part I* (pp. 263–270). Amsterdam: North-Holland.
26. Khan, G., Sarstedt, M., Shiao, W.-L., Hair, J. F., Ringle, C. M., & Fritze, M. (2019). Methodological research on partial least squares structural equation modeling (PLS-SEM): A social network analysis. *Internet Research*, 29(3), 407–429.
27. Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261.
28. Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences*, 52(2), 362–292.
29. Reinartz W.J., Haenlein M., Henseler J. (2009) An Empirical Comparison of the Efficacy of Covariance-Based and Variance-Based SEM (SSRN Scholarly Paper No ID 1462666), Rochester, Y: Social Science Research Network.
30. Rigdon, E. E. (2012). Rethinking partial least squares path modeling: In praise of simple methods. *Long Range Planning*, 45(5–6), 341–358.
31. Rigdon, E. E. (2016). Choosing PLS path modeling as the analytical method in European management research: A realist perspective. *European Management Journal*, 34(6), 598–605.
32. Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *International Journal of Human Resource Management*, 31(12), 1617–1643.

33. Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research*, 69(10), 3998–4010.
34. Lohmöller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Heidelberg: Physica.
35. Mateos-Aparicio, G. (2011). Partial least squares (PLS) methods: Origins, evolution, and application to social sciences. *Communications in Statistics - Theory and Methods*, 40(13), 2305–2317.
36. Rigdon E.E. (2012) Rethinking partial least squares path modeling: in praise of simple methods. *Long Range Planning*, 45, 341–358. DOI: 10.1016/j.lrp.2012.09.010.
37. Rigdon, E. E., Becker, J. M., & Sarstedt, M. (2019). Factor indeterminacy as metrological uncertainty: Implications for advancing psychological measurement. *Multivariate Behavioral Research*, 54(3), 429–443.
38. Willaby, H. W., Costa, D. S. J., Burns, B. D., MacCann, C., & Roberts, R. D. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology, *Personality and Individual Differences*, 84, 73–78.

## نمذجة المعادلة الهيكلية للمربعات الصغرى الجزئية لتحديد تأثير بعض العوامل المختارة على أداء الأعمال

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**الخلاصة:** اكتسبت جزئية المربعات الصغرى النمذجة المعادلة الهيكلية (الثابتة والمتنقلة-وزارة شؤون المرأة) شعبية كوسيلة لتقدير (معقدة) نماذج مسار مع المتغيرات الكامنة وعلاقاتهم. في دراسة بحثية أجريت في أبوجا ، تم استخدام سمارت بلس 4 البرمجيات للتحقيق في آثار عوامل مختارة على أداء الأعمال والنمو في أربعة أسواق رئيسية: سوق غاركي ، سوق ووس ، سوق ديدي ، وسوق السمك كادو. شملت الدراسة أصحاب الأعمال الذين يعملون في تجارة التجزئة أو الإمدادات أو التوزيع أو البيع بالجملة في هذه الأسواق. تم توزيع استبيانات حول العوامل التي تؤثر على أداء الأعمال ونموها بين أصحاب الأعمال ، وقدمت ردودهم بيانات ديموغرافية ومعلومات عن المتغيرات الكامنة. وكشف التحليل أن الأفراد والأسرة وبيئة الأعمال والمؤسسات المالية والحكومة تؤثر بشكل كبير على أداء الأعمال ونمو أصحاب الأعمال.

**الكلمات المفتاحية:** جزئي أقل مربع الثابتة والمتنقلة ، (نمذجة المعادلة الهيكلية (سيم) ، سمارت بلس 4 ، البرمجيات ، متغير كامن.