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Numerical Analysis of Next-Generation Wireless Networks Using Modified PLS-SEM Model

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ABSTRACT

In this paper, three constructs are initialized in conventional Structural Equation model (SEM) to minimize large-scale extensive pre-deployed model simulations in wireless networks while observing subscribers' behavior to an active network. These constructs are directly connected to subscriber's sense of judgement on active and adopting next-generation networks. Our model is developed using SEM and estimated using Partial least square (PLS) to establish one Partial Least Square-Structural Equation Model (PLS-SEM) to overcome collinearity problem of SEM approximations. Model is validated on 4G network data sets, which are captured from rural and urban areas of Kano. Performance of the models was verified using Cronbach's Alpha, rho_A, composite reliability and average variance extracted (AVE) to confirm reliability and validity. The Cronbach's alpha, rho_A, composite reliability, and validity achieved threshold point of 0.7, 0.7, 0.7 and 0.5, respectively. The formulated hypothesis is significantly established with coefficient of determination (R^2) of 94.4% and 96.5% for dependent variable Behavioral Intention (BI) and Facilitating Conditions (FC).

Keywords: Next Generation Networks, Network adoption, UTAUT model, PLS-SEM, Statistical Model, 4G Network.

1. INTRODUCTION

Ever-increasing demand for wireless communications pave ways to multimedia services, internet of things, robotic applications etc., [1] and it widens broadband access proliferation from one generation to another as illustrated in Figure 1. This proliferation rise active 4G internet subscribers to more than 8 billion [2] & [3]. The 4G network is globally deployed to resolve hindrance by its preceding 3G network's instability, restricted mobility, and bandwidth shortage [4], [5]. Success of next generation wireless networks depend on 4G subscribers' contentment and affordability to cater their multimedia communication demands etc. Therefore, it is demonstrated that 4G network is critical digital mobile communication infrastructure to determine future survival of internet of things (IoT) [6], smart technology, and progressing 5G network, thus pose a need to analyze factors that hinders 4G network survival. However, challenges that defeats survival of 4G network among others are perceived subscriber behaviors. Subscribers spend time and money to explore possibility of adopting or rejecting new wireless networks. Network rejection is a fundamental and burdensome problem in deploying new wireless networks, which cost network carriers a large-scale extensive model simulations of network parameters (observational variables) [7]. These models are normally built to understand customers attitude before deployment of new network. However, the models need careful observation, because of uncertainty due to observation variables are modeled mathematically. However, observational uncertainty occur due to structural uncertainty and uncertainty from observing modeling parameters [8]-[9]. Therefore, previous studies address large-scale simulation problems using numerical statistical simulations from real data within environment of deployment and display promising result to accurately map inputs and outputs of real phenomenon according to Structural Equation Model (SEM) to understand subscriber's behavior on real applications [10],[11], [12], [13] and [14]. However, these models were restricted to some regions and were not tested on the data set of our case study areas.

In this paper, we propose constructs from 4G wireless network data set in SEM and estimated using Partial least square (PLS-SEM) model to analyze subscribers attitude towards existing and next-generation wireless networks and to overcome collinearity problem of SEM approximations.

SEM is one kind of numerical statistical model having set of equations with concomitant assumptions for system analysis, where parameters of systems are realized according to statistical observation [12]. SEM is flexible to variable that serves as endogenous variable in one model and as well functions as an exogenous variable in another model. Therefore, variables that are not measured directly are included in SEM models, though are added indirectly through its effects or observable causes. SEM is constructed using different computer packages and is applied widely in many fields such as in engineering, science, sociology, biostatistics, etc [15]. However, exists numerous statistical approaches to approximate SEM model such as weighted least square, diagonally weighted least square, maximum likelihood [13] etc. however approximation using the mentioned approaches need large normally distributed data samples [16]. To overcome these drawbacks, researchers come up with partial least square (PLS) technique.

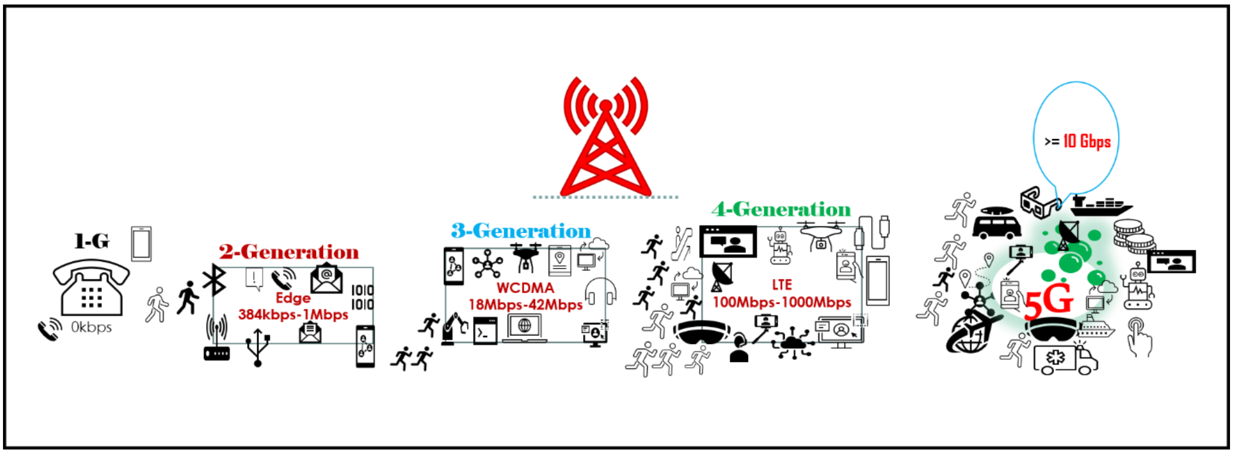

Figure 1. Proliferation of Wireless Mobile Communications across Generations.

Partial Least Square (PLS) is a machine learning-based approach that maps correlation among set of observations with latent variables. It has several advantages in multilinear regression of being optimal and efficient. PLS with SEM is integrated as one model (PLS-SEM), and adopted in theory development to analyze chosen constructs to a defined target [17]. The major advantages of using PLS approach over the existing SEM approximation, it set minor boundaries on the calibrated scales, residual distribution, and sample size which are suitable for our research. It could help in analyzing chosen hindrance variables to acceptance of the existing 4G network and would further manifest to catastrophic technology repudiation (attitudes of rejecting adopted network) in the fourth-coming beyond 5G network [18]. Furthermore, new networks rejection problem raised several research questions regarding the reasons why network subscribers decide to or not adopt 4G or new networks? and what factors that influence such decisions? The models that try to address these issues are classified as: statistical regression-based methods, and multi-criteria decision making. However, methods that applied linear regression model did not utilized independent variables effectively, as formulated in equation (1), thus sensitive to co-linearity. Multiple regression model computed beta value not directly from test as formulated in equation (2), it is error-prone technique in case of negative beta. Multi-criteria decision lack dimensionality due to cause and effect relationships among technology adoption factors [14]. Multicriteria decision has rank flip-flop issues and require considerable precise input [19], . SEM issues would be overcome using Unified Theory of Acceptance and Use of Technology (UTAUT) model is preferred.

It can be demonstrated in previous works that books conventional SEM using UTAUT models such as [20] [21], [22], [23], [24], [25], [26], [27], and [28] suitability and superiority of adopting UTAUT latent variables with their new developed variables to learn online and offline mobile technology acceptance. However, conventional SEMs involve multiple series of statistical tests before modeling, and need covariance-based SEM for normality, as exist non-normal to most of the end-user behavioral research dataset. Recently, extended Diffusion theory to mobile telecommunications technologies (MTTs), to understand social complex structure on Iran telecom industries is adopted in [29]. Ref [17], [30], [31], [32], [33], [16], [34], [35], [22], [36] [37], [31] designed a framework to utilized UTAUT constructs in an unnatural/natural environments using PLS-SEM, in which the papers output promising results and indicate that PLS-SEM serve as valuable tool in predicting users' behavior of existing and approaching new wireless technology.

SEM Approaches for 4G network adoption: Ref [4] extracted variables in web-based questionnaire and statistically analyzed using SEM with maximum likelihood approximation. This finding confirms that UTAUT model is promising for subscribers' pattern to 4G network adoption. According to authors perceived usefulness facilitate subscribers' intention towards 4G network, whereas uncertainty negatively influence transaction costs. Their method is sensitive to large normally distributed data samples. Ref [14] identified key critical success factors to facilitate 4G networks adoption in Iran using fuzzy DEMATEL model. In ref [38] evaluates general SEM model using perceived utility of a new technology and perceived utility of a new service to track subscribers' perception and intention to adopt new technology, though this approach reported significant results of adopting latent variables, however SEM approximation using maximum likelihood is sensitive to normally distributed data, which give lot of statistical tests. Perceived cost is a strong indicator of subscribers' behavioral intention to adopt new technology, as evaluated using PLS-SEM approach in [39]. PLS-SEM approach is initialize in our research to overcome drawbacks of SEM approximation with maximum likelihood as motivated in [4], [38], PLS-SEM has superiority of being flexible to distributional assumptions and can deals with sophisticated forecasting attributes [17]. PLS is unbound by normality assumption. The prediction of PLS as compared to conventional SEM approximation can handle prediction error very well. It takes into account complex statistical analysis and cross-relationships among multiple variables [39]. The UTAUT general model adopted by the existing methods comprised of performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), social influence (SI), behavioral intention (BI), and usage behavior (BU) and four moderating variables: age, gender, experience, and voluntariness usage [32]. In this our approach, we initialized transmission speed and PE as independent variables into BI as constructs to UTAUT model. The second model is made by initializing uncertainty and transaction cost [4] as independent variables into FC as constructs to UTAUT model. The constructs give more confidence about the subscriber has upon network carriers. These constructs are directly connected to subscriber's sense of judgement to existing and new wireless networks. Our models treated moderating variables independently, to have full representation of subscribers on new network adoption and their behavior pattern. For more details of UTAUT model refer to [40].

1.1 Motivations for the PLS-SEM

Our model is observationally validated to 4G networks around urban and rural areas of Kano state, Nigeria. Nigeria is situated along central and western parts of Africa, with largest human population in Africa approximately 200 million, largest economy in African continent, peak natural gas reserves and has one of youngest populations on earth [41], these factors make it avenue to harness potentials of 4G and next-generation wireless network. As reported by the international telecommunication union (ITU) that "an increase of 10% in mobile broadband penetration yields an increase in 2% in GDP" [42]-[43]. According to United Nations Conference on Trade and Development (UNCTAD); "Nigeria's e-commerce spending is projected to increase to $75 billion by 2025 and these platforms could be created through support for service infrastructure pillar as key role in this projection" [43]. However, motivated by government's approval to launches first 4G long term evolution (LTE) networks since, February 25, 2016 [44] and the benefits of adopting new fourth-coming wireless networks, it is very crucial to evaluate the network current state-of-the-art and to insight subscribers behavior to adoption of fourth-coming technology in the Nigerian context. 4G cellular networks are present active network in Nigeria. Peculiar characters of 4G mobile carriers in Nigeria and effect of conspicuous internet data consumption, as reported by subscribers in Table 1, lead problems towards acceptance of 4G wireless cellular network [45]. Attraction towards fast approaching of 5G wireless network services [18] could be fulfilled from existing network, but this effort is facing rejection from masses due to inability to maintain efficient 4G wireless network as shown in Table 1 and Figure 2. The Nigerian Communication Commission (NCC) introduce many policies in the year 2021 to meet subscriber's satisfaction. It claims that out of 3019 registered complaints, 2995 were adequately attended which shows great success than that of 2020 [46]. As reported in [46], the active mobile internet subscriptions to be put in more than 40 million in conventional networks as illustrated in Figure 3, but unfortunately half of these populations are not active on emerging 4G network, and out of this population few number of subscribers continue to use 4G network once adopted. To entice this segment of subscribers, mobile carriers enunciate benefits of 4G network, features, price, and affordability of the 4G-enabled handsets. However, both rejection behavior factors and new network adoption are affected by not only facilitating condition, behavioral intention, but also dictated by uncertainty, and transmission speed and other factors associated with services and physical devices needed to accept the 4G network.

However, these trending issues cannot be underestimated, as it critically affecting subscribers, government's digital economy plan and digital ICT proliferation in the country. As we know, this is the first research in Nigeria that scientifically analyze subscribers' behavior map to adoption of new wireless network, according to theoretical framework of Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Motivational Model (MM), Innovation Diffusion Theory (IDT), Model of PC Utilization (MPCU), Social Cognitive Theory (SCT), and the hybrid models [40], [47], [20], [39], [45]. In recent years, these eight models were built together as a single Unified Theory of Acceptance and Use of Technology (UTAUT) model [40] to achieve notable advantages over existing individual models.

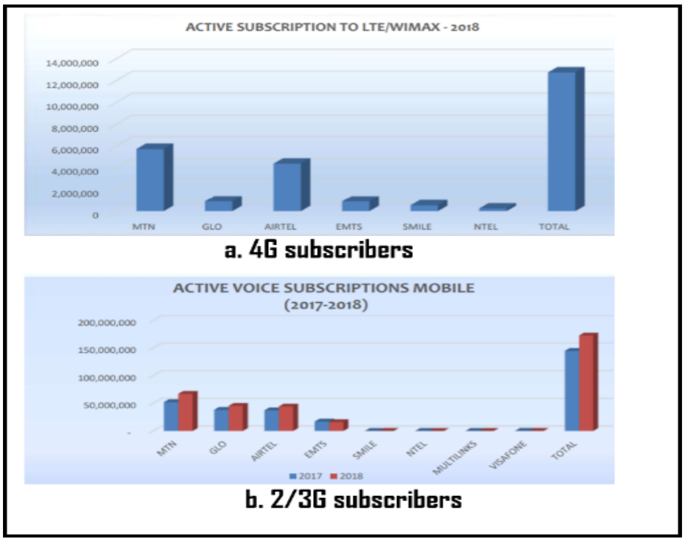

Figure 2: **a.** Active new 4G LTE network subscribers **b.** Active conventional 2G/3G networks subscribers [46].

Table 1. Complaints Received by NCC during the lockdown period on the peculiar character and Veblen effect of mobile carriers in the country [48].

Data	Billing	SIM Registration	Credit Depletion	VAS	Line Barred	Poor Network	Fraud	Total
58	3	2	5	3	2	2	1	76

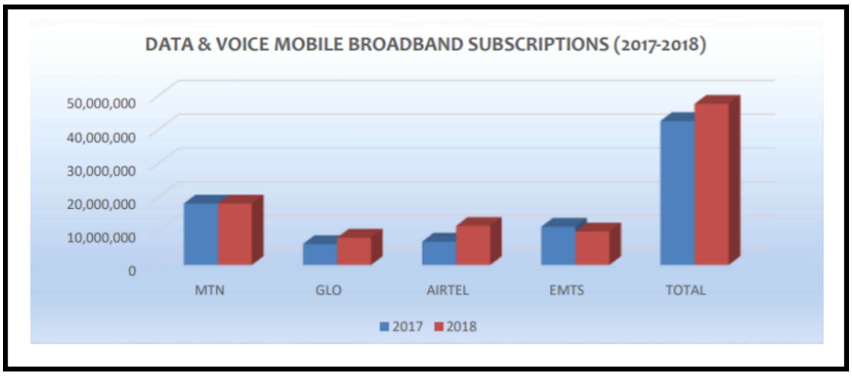

Figure 3: Data and Voice Mobile Broadband Penetrations across the country [46]

1.2 Problem Formulations

We first formulate concept of SEM approximation using linear regression and finally formulate partial least square approximations. For simple linear regression, where b and a are endogenous and exogenous variables, respectively. λ is regression coefficient. $\in$ denotes the error term, then.

$$b = \lambda a + \in \qquad (1)$$

if $(b) = E(a) = 0$, taking into consideration the regression assumptions and multiplying the equation by a, then

$$ab = \lambda a^2 + a \in, \qquad (2)$$

where $E(ab) = \lambda E(a^2) + E(a \in)$

$$Cov(a, b) = \lambda Var(a^2) + Cov(a \in) \qquad (3)$$

$$\rho_{ab} = \lambda \rho_a^2 + 0, \qquad (4)$$

$Cov(a \in) = 0$, if a and $\in$ are independent.

Therefore, $\lambda = \frac{\rho_{ab}}{\rho_a^2}$ (5)

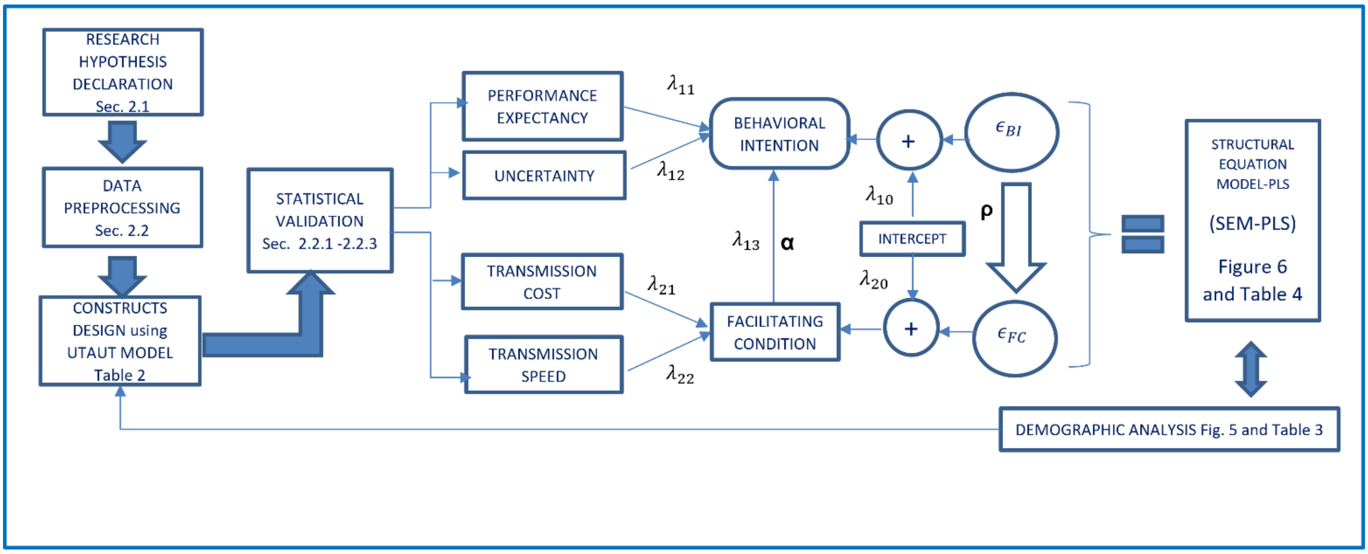

Figure 4. Our Proposed Model with Constructs estimation

However, a general multiple regression equation is formulated as follows,

$$b = \lambda_o + \lambda_1 a_1 + \lambda_2 a_2 + \cdots + \lambda_n a_n + \in_i \qquad (6)$$

Assuming $\in_i$ to be independent and identically distributed normally (iid) and multiplying both the equations by $x1$ and $x2$.

$$\rho_{x1y} = \lambda_1 \rho_{x1}^2 + \lambda_2 \rho_{x1x2} + 0 \qquad (7)$$

$$\rho_{x2y} = \lambda_1 \rho_{x1x2} + \lambda_2 \rho_{x2}^2 + 0 \quad (8)$$

Familiar steps of substituting sample estimators can be used to obtain the coefficients of the models.

$$\in \sim iid\ (0,1)$$

Equivalently, ordinary least square (OLS) estimator is formulated as

$$b_{OLS} = (X'X)^{-1}X'\mathrm{Y} \qquad (10)$$

As in accordance, we can formulate our SEM model using.

$$BI_i = \lambda_{10} + \lambda_{11}PE_i + \lambda_{12}UT_i + \alpha FC_i + \epsilon_{BIi} \quad (11)$$

Where

PE_i , UT_i , TC_i and TS_i are Explanatory variables, FC_i and BI_i are response variables, λ's is structural coefficients of an Explanatory on response variables, variable α is structural coefficients of response variables on variable response and ϵ_{BIi} and ϵ_{FCi} are error terms.

$$FC_i = \lambda_{20} + \lambda_{21}TC_i + \lambda_{22}TS_i + \epsilon_{FCi} \qquad (12)$$

And these can be re-written as

$$BI = \lambda_{11}PE + \lambda_{12}UT + \alpha FC + \epsilon_{BI} \qquad (13)$$

$$FC = \lambda_{21}TC + \lambda_{22}TS + \epsilon_{FC} \qquad (14)$$

The Assumption of collinearity must be sustained for the estimation equation to have a Uniqueness property.

Estimation using Matrix.

Given the equation.

$$B_{(n\times 1)} = A_{(n\times k+1)}\lambda_{(k+1\times 1)} + \in_{(n\times 1)} \qquad (9)$$

However, PLS-SEM equations (11)-(14) can be approximated using equation (15), with Q_{mn} , σ_{lm}, ρ_{lmn}, and ϵ_{mn} , respectively, denotes scores of latent variable which can be updated by the weighted sum of the variables on the right, updated weights, indicators, and error terms, respectively.

$$Q_{mn} = \sum_{lm} \sigma_{lm}\rho_{lmn} + \epsilon_{mn} \qquad (15)$$

Formulated hypothesis is tested theoretically and numerically to hypothesized relationship, using structured questionnaire adopted to legitimate network subscribers at various locations in urban and rural areas of Kano State-Nigeria. Equations (11)-(14) better explains our constructed model. Moderating variables were statistically analyzed independently to indicates idiosyncrasy contribution to 4G and next generation network.

2. MATERIALS AND METHODS

In this section, we present experimental validation of PLS-SEM according to UTAUT concept. We declare research hypothesis (Section 2.1). We describe data preprocessing (Section 2.2); confirmatory, reliability analysis, validity analysis, Cronbach's alpha, average variance extracted (AVE), and composite reliability. and finally present data training phase (Section 2.3). The flow chart of the proposed concept is shown in Figure 4.

2.1 Research Hypothesis Declaration

This research study will be built based on the following declared hypothesis.

H1: Behavioral Intention has no positive relationship with Facilitating Conditions.

H2: Transmission Speed has no positive relationship with Facilitating Conditions.

H3: Performance Expectancy has no positive relationship with Behavioral Intention.

2.2 Data Preprocessing

The dataset in our research is collected by administering comprehensive questionnaire according the UTAUT model to four wireless network carriers (I, J, K and L networks) as described in Table 2. The legitimate names of these networks remain confidential for security and research reasons. The answers to questionnaire were first encoded from 1-6. The extracted dataset is categorized into six latent variables: (1) Transmission speed (TS) which is obtained through three structured factors. TS includes data speed experience from both uplink and downlink rate, (2) Performance expectancy (PE) is curated through six structured factors, (3) Uncertainty (UT) which is obtained through four structured factors, (4) Transaction cost (TC) which is obtained through four structured factors, (5) Behavioral Intention (BI) is which obtained through three structured factors, and (6) facilitating condition (FC) is curated through three structured factors. We obtained the control variables through four demographic constructs. Dataset is not expected to appear perfectly. Data preprocessing involve cleaning data from any threats, missing values, outliers, and human errors. We subject dataset to undergone missing check, and missing values were replaced manually by the mode of the answers (though, SmartPLS takes care of the missing values, but there were replaced for future consumptions). However, duplication values were checked and removed to avoid distorted result. We further conduct the following tests.

2.2.1 Confirmatory factor analysis (CFA) is carried out to calibrate measured model in terms of reliability, internal consistency and calibrate observed variables [17]. CR is used as more representative to internal consistency, as it memorize the standardized loadings of the observed variables [17]

2.2.2 Reliability Analysis: It is defined as the extent to which a subscriber trusts calibrated results, which includes constancy and consistency, the suggested target is 0.7. For the purpose of this paper, we evaluated Cronbach's alpha coefficient [21]. The value of this metric is 0.81 which demonstrated high reliability and enable further analysis.

2.2.3 Validity Analysis: This is defined as the extent to which the calibrated results reflect the actual calibrated target and achieve the required decision [21], the suggested target is 0.7. For this paper, we evaluated Extracted Average Variance value (AVE). However, Cronbach's alpha and composite reliability (CR) are used to assess internal ability of the measurands. Whereas average variance extracted (AVE) is used to demonstrates convergent validity [22].

Table 2. Constructs Items

S/No.	**Constructs Measurement**
1.	Transmission Speed 1. I could use the network and it accessory as internet router and modem if I could get knowledge of the 4G network. 2. How faster are your service provider? 3. Which smartphone brand you are using.
2.	Performance Expectancy 1. Using the 4G network is useful in my career/work. 2. If I would use the 4G network, can enable me to achieve work performance. 3. It would uplift my exposure to the digital world. 4. Using 4G network would solve my present internet service failure. 5. Using the 4G network would save my traditional internet service subscriptions cost efficiently. 6. If I would use the 4G network, would speed up my internet services.
3.	Uncertainty 1. I believe it would be dangerous to trust the carriers. 2. I am afraid to obtain the 4G resources, I would not have the 4G network connection on my location. 3. I would not trust the carriers. 4. I would trust the carriers.
4.	Transaction Cost

	1. I could buy the phone and subscribe to the network if an affordable price is tag. 2. I am afraid to obtain the 4G resources, I could not have skill/expertise to operate the phone. 3. I believe that using the 4G network would consume much data than the 3G network 4. There is restriction and compatibility issues with my 3G network terminal.
5.	Behavioral Intention 1. I could use the network and its terminal if it becomes accessible and obtainable (practicable). 2. I decide to use the network, since I had access it. 3. I intended to use 4G network frequently
6.	Facilitating Conditions 1. The 4G network and its resources are practically realizable. 2. I have the 4G network-enabled phone. 3. Support services/customer care could be available for complaints and grievances.
7.	Control Variables 1. Age 2. Gender 3. Education 4. Mobile Operator Used

2.3 Data Training

The research train six (6) latent variables (TS, PE, UT, TC, BI, and FC), as illustrates in Table 2. The latent variables were built in Equations (5) through (6). The training is performed using SmartPLS software package. The package houses different statistical tools that comprises of linear model, factor loadings, path analysis and multiple regression [49]. BI and FC were considered as dependent or exogenous variables, these were initialized from equations (11) through (14). As stated earlier, model training is established using PLS-SEM approximation. The variables were carefully and adequately chosen to avoid falling into over-fitting and under-fitting of the model as described in Section 2.1.

3.0 RESULTS AND DISCUSSION

In this section we present both qualitative and quantitative evaluations of experimental results.

3.1 Demographic Characteristics Analysis

According to the observed data, 77% of the respondents are male and 23% are female. This shows that majority of the respondent aged between the range of 18-25yrs. The respondents are majority J network subscribers with 69%, seconded by K network having 19.5%. Therefore, Figure 5 depicted distributions of data according to the population of our respondents. Table 3 indicate the respondents' population.

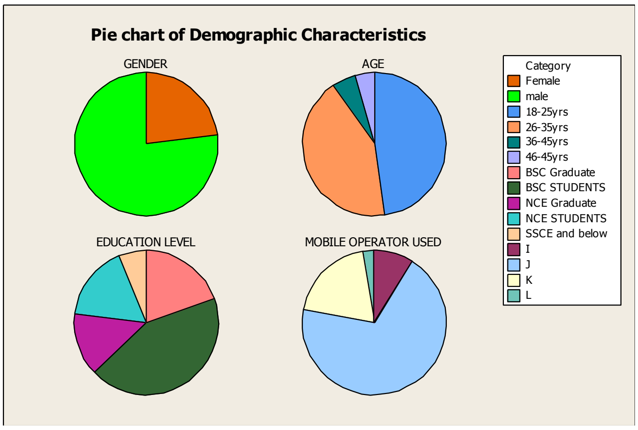

Figure 5. Distributions of the respondents' population.

These can simply say that most of the respondents are male University students at the age range of 18-25 years and are using MTN network.

Table 3. Demographic Characteristics Analysis

		Frequency	Percentage (%)
GENDER	Male	87	77.0
	Female	26	23.0
	Total		100.0
AGE	18-25yrs	54	47.8
	26-35yrs	45	42.5.
	36-45yrs	9	5.3
	46-above yrs	5	4.4

	Total	113	100.0
MOBILE CARRIER USED	I	10	8.8
	J	78	69.0
	K	22	19.5
	L	3	2.7
	Total	113	100.0
EDUCATION	SSCE and below	7	6.2
	NCE students	19	16.8
	BSC students	49	43.4
	NCE graduate	16	14.2
	BSC graduate	22	19.5
	Total	113	100.0

3.2 Verification of the Models using Reliability and Validity

Our model found PE, UT, and TC to have great impact to behavioral intention and on the other side; BI and FC were found to influence the use of new wireless networks.

According to table 4, the reliability of the constructs which measures the consistency and stability of the constructs is assessed using Cronbach's Alpha with a threshold point of 0.7. it indicates all the values are above threshold point. Figure 6 contains inner and outer loadings and coefficients of determination of the constructs

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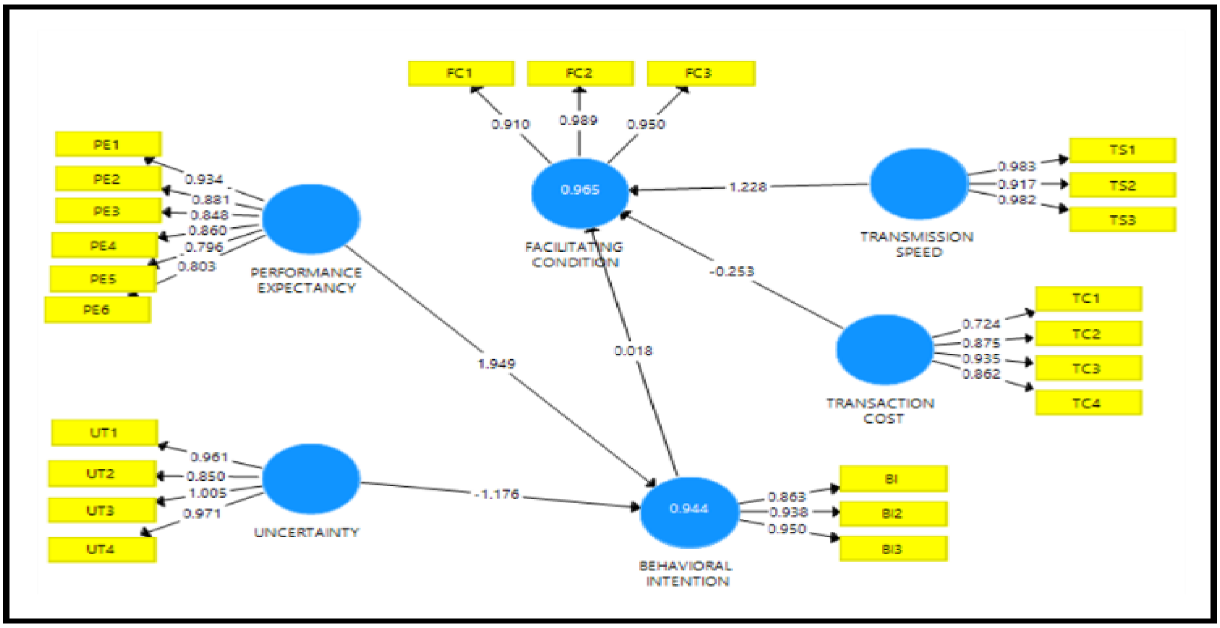

Figure 6: PLS Algorithms of the Constructs

Table 4. Factor Loadings

S/N	CONSTRUCTS	ITEMS	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
1	BEHAVIORAL INTENTION	BI1	0.863	0.940	0.943	0.941	0.842
		BI2	0.938				
		BI3	0.950				
2	FACILITATING CONDITION	FC1	0.910	0.965	0.967	0.965	0.903
		FC2	0.989				
		FC3	0.950				
3	PERFORMANCE EXPECTANCY	PE1	0.934	0.942	0.944	0.942	0.731
		PE2	0.881				
		PE3	0.848				
		PE4	0.860				
		PE5	0.796				
		PE6	0.803				
4	TRANSACTION COST	TC1	0.724	0.908	0.921	0.914	0.727
		TC2	0.875				
		TC3	0.935				
		TC4	0.862				
5	TRANSMISSION SPEED	TS1	0.983	0.973	0.975	0.973	0.924
		TS2	0.917				
		TS3	0.982				
6	UNCERTAINTY	UT1	0.961	0.972	0.976	0.973	0.900
		UT2	0.850				
		UT3	1.005				
		UT4	0.971				

Table 4 indicates that, outcomes of convergent and discriminant validity is attained when the factor loadings factor is above 0.7, as it ranges from 0.724 for transmission cost (TC1) to 0.989 for facilitating condition (FC2). The convergent and discriminant validity can be assessed using Average variance extracted (AVE), rho_A and composite reliability with a threshold point of 0.5, 0.7 and 0.7, respectively.

3.3 Model Significance

Considering Table 5. Performance Expectancy (PE) and Uncertainty (UT) indicate statistical significance to Behavioral Intention (BI) having a P-Value of 0.000 while transmission speed (TS) has significant relationship with facilitating Conditions (FC) having a P-Value of 0.000. Figure 7 contains P-values for the inner and outer model. The transaction cost has weak relationship with facilitating conditions.

Table 5. Significance of Variables

	COEFFICIENTS	STANDARD ERROR	T Values	P Values
BI -> FC	0.018	0.082	0.214	0.831
PE -> BI	1.949	0.56	3.479	0.001
TC -> FC	-0.253	0.289	0.876	0.381
TS -> FC	1.228	0.249	4.935	0.000
UT -> BI	-1.176	0.578	2.035	0.042

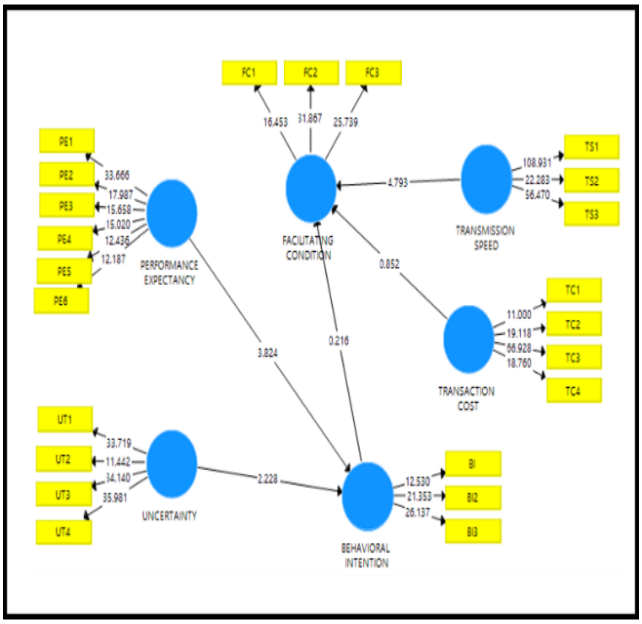

Figure 7. PLS Bootstrapping of the Constructs

3.4 Model Fitness

With a 94.4% as R^2 (coefficient of determination) for dependent variable BI and 96.5% as R^2 for dependent variable FC, it means 94.4% and 96.5% of the variation is explained by the models, respectively. This is to say that variations are adequately explained. Also, the SRMR (Root Mean Square Residuals) is calculated to be less than 0.08, which shows a good model-fit.

3.5 Comparison of Results to Some existing works

Our proposed method outperforms some of the existing methods in the literature, Table 6 refers.

Table 6. Results Comparison with some existing methods, the Bolded one is the best result.

Method	Construct name	Value of R^2	Interpretation
Hassan et al [39]	Behavioral Intention	0.355	Moderate
Lin et al. [4]	Behavioral Intention	0.865	Strong
Our approach	**Behavioral Intention**	**0.944**	**Strong**

4.0 Conclusions

Increase rate in adoption of existing 4G and next-generation wireless network, is associated with three key constructs: TS, PE, TC, and uncertainty. It is investigated that PE remains a key to determine subscribers' behavioral attitude. While an effective TS to entice subscribers in adopting 4G networks and next-generation network is significant. Our study expected TC as hindrance factor towards adoption of 4G network, however contradicted with assumption [4]. In general, the proposed models fully represented subscribers' repudiation technology pattern and fulfill our research assumptions. However still accessing 4G network service is location dependent in the study areas. In terms of policy making, making 4G network in Nigeria to obtain reliable service rate, could leads to high visibility to urban, rural, and sub-rural areas. It would facilitate subscribers to switch uncertainty and embrace any future networks. Therefore, reliable 4G network service enables IoT opportunities and provide enabling environment to fast-approaching 5G network to Nigeria.

However, failure to address mentioned factors, may lead to lack the technological integrability of 5G and next generation network, thereby losing IoT opportunities, revenue, and unable to accommodate all the existing network subscribers. These could not only affect network carriers but the government's national digital economy policy and strategy plan. The approach opens road to understanding of 5G and next-generation wireless networks adoption because of numerous benefits and flexibility. Our model could serve as evaluation metrics to subscribers' trajectory and network carriers in solving trending issues of new wireless networks adoption. Hopefully, the result of this study could contribute to the literature of the UTAUT model in the context of developing countries.

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