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INVESTIGATING THE IMPACT OF COVID-19 LOCKDOWN ON WORK-ATTRIBUTES OF PHARMACEUTICAL SALES REPRESENTATIVES THROUGH EXPLORATORY FACTOR ANALYSIS

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Article Info

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Abstract

Factor analysis is a widely used quantitative technique in various disciplines, including the social, behavioral, and management sciences. It helps simplify complex data, reveal relationships among seemingly unrelated variables, and reduce data without losing essential information. While factor analysis has been extensively applied in many fields, its applications in social and administrative pharmacy research, particularly in pharmaceutical sales and marketing practice, have been largely untapped. This study aims to address this research gap and explore the use of factor analysis in the pharmaceutical sales and marketing industry, focusing on the effects of the COVID-19 pandemic on the work-attributes of pharmaceutical sales representatives (PSRs).

Given the rapidly changing paradigm in the pharmaceutical industry due to the pandemic, understanding the impact on the roles and functions of healthcare supply chain staff, specifically PSRs, is crucial. By employing factor analysis, this study seeks to derive constructs that aid in the characterization, understanding, and prioritization of these work-attributes. The research utilizes exploratory factor analysis (EFA) on data obtained from a structured questionnaire administered to a pool of PSRs in Nigeria. The questionnaire assesses the perception of PSRs regarding the relevance of work-attributes during the COVID-19 lockdown.Two methods of factor extraction, namely Principal Component Analysis (PCA) and Principal Axis Factoring (PAF), are employed to analyze the data and compare the results from different analytical perspectives. The primary objective is to generate parsimonious elements of the constructs and gain insights into the impact of the pandemic on the work-attributes of PSRs. The findings of this study contribute to the existing literature on factor analysis and provide valuable insights for pharmaceutical sales and marketing practitioners, particularly in the context of the COVID-19 pandemic.

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1. Introduction

Factor analysis is a structural equation (quantitative) technique used to simplify, further explain large, complex data, and generate linked relationships that may occur among a set of seemingly unrelated observed variables (Reio Jr & Shuck, 2015; Thompson, 2004). Factor Analysis has been extensively applied in many disciplines especially in the social, behavioral, and management sciences (Nimalathasan, 2009) relationship marketing research for large data reduction without loss of essential information (Luigi, Ţichindelean, & Vinerean, 2013) education research studies (Ozturk, 2011) practice research (Schreiber, 2020; Van De Tran, 2019; Watterson, Look, Steege, & Chui, 2020): research guidelines for factor analytic studies (Berliner, 2002; Goretzko, Pham, & Bühner, 2019; Matsunaga, 2010; Nimalathasan, 2009; Schreiber, 2020).

Several reporting algorithms have been proposed in the literature for properly conducting factor analysis (FA) in social, management, and behavioral sciences (Goretzko et al., 2019; Matsunaga, 2010; Ozturk, 2011; Schreiber, 2020). However, in social and administrative pharmacy research, particularly in pharmaceutical sales and marketing practice, there are many untapped applications of this quantitative tool (Schreiber, 2020; Van De Tran, 2019; Watterson et al., 2020).

Furthermore, there is an increasing demand for research in the pharmaceutical sales and marketing industry relating to the effects of the COVID-19 pandemic, where the paradigm of job description and processes is rapidly changing as firms and employees continue to adapt to these effects daily. It is useful to have a better understanding of how this paradigm shift affects the work-attributes of healthcare supply chain staff, in particular, pharmaceutical sales representatives (PSRs). This perhaps will support characterization into constructs to aid proper understanding and prioritization of roles and functions, as required. Hence, the use of quantitative techniques such as Factor analysis (FA) to derive constructs, facilitate parsimony, understanding, and as well as acquire the desired skill set for practitioners.

Therefore, the main purpose of this empirical study is the application of exploratory factor analysis (EFA) to the responses' obtained from a 13-item structured questionnaire administered to a pool of pharmaceutical sales representatives (PSRs) in Nigeria. Study questions were used to assess PSRs' perception of the relevance of work-attributes or characteristics during the period of COVID-19 lockdown in Nigeria. This study employed the use of two methods of factor extraction: Principal component analysis (PCA) versus Principal axis factoring (PAF) methods respectively. The rationale was aimed at evaluating from two analytical perspectives, the output of factor extraction with the primary objective of generating parsimonious elements of the constructs.

1.1. Conceptual Framework of the Study

Pharmaceutical sales representatives are involved in the supply chain of pharmaceutical products, services, and medical information dissemination. Their core responsibilities include drug/product information services, drug supply, interaction with healthcare professionals (HCPs), and a critical interface between drug retailers and the final consumer or patient (Oamen, 2021; Obuaku, 2014; Ugbam & Okoro, 2017; WHO, 2010)**.** However, the occurrence of COVID-19 has by effects, expanded the role and operations of PSRs to include other related work-attributes about: issues with access to health care professionals (HCPs), involvement in COVID screening, business operations remodeling, and community engagement (Ayati, Saiyarsarai, & Nikfar, 2020; Elbeddini & Yeats, 2020; Gray, Hoffman, & Mansfield, 2020; Oamen, 2021).

Therefore, this study empirically assessed the perception of respondents about the relevance of their multi-faceted work-attributes in the face of COVID-19 lockdown and restrictions as experienced in many countries, globally. A study of pharmaceutical sales representatives' perception of the relevance of the overall work attributes in Nigeria using exploratory factor analysis (EFA) is thus required. In this study, two extraction perspectives were deployed; Principal Component Analysis (PCA) and Principal Axis Factoring (PAF). Several studies have raised methodological arguments about the relevance and applicability of factor extraction methods; PCA and PAF. While some advocate the use of PCA to develop parsimony and constructs (Henson, Capraro, & Capraro, 2004; Pett, Lackey, & Sullivan, 2003; Tabachnick & Fidell, 2007). Other studies suggest the use of PAF based on the premise that there could be some correlation or causal relationships among items/variables in a given study and hence generalizable to the general population (Conway & Huffcutt, 2003; Izquierdo, Olea, & Abad, 2014; Kahn, 2006; Mvududu & Sink, 2013). This study applied both methodological perspectives in its factor analysis modeling to draw relationships and possible correlations between the observed variables and latent (unobserved variables). Therefore, this exploratory analysis provided the theoretical context for further model fit validation of research instruments using Confirmatory Factor analysis (CFA). It is the focus of this study that more research evaluations in pharmaceutical sales and marketing Industry should adopt this quantitative research technique.

1.2. Objectives of the Study

The main objectives of this study are enumerated as follows;

1. Evaluate the perception of the relevance of work-attributes of PSRs using exploratory factor analysis.
2. Use outcome/s of study to produce a working Factor analysis framework for application in pharmaceutical sales and marketing research.

1.3. The hypothesis of the Study

The hypothesis of the study was stated in the null as follows:

1. *HO1: There is no confirmed measure of construct validity or reliability from the dataset for exploratory factor analysis to be performed adequately.*
2. *HO2: There is no difference in the output of factor extraction methods; Principal component analysis (with varimax rotation) versus Principal axis factoring (with Promax) method.*
3. *HO3; There is no significant difference between the actual eigenvalues from the dataset and simulated eigenvalues output of Parallel Analysis (PA).*
4. *HO4: There is no meaningful ranked difference between observed variables (work-attributes) in each determined constructs.*

2. Research Methodology

2.1. Questionnaire Design

The questionnaire survey method was adopted for this research as a tool to collect required empirical data. A total of 13-survey items were generated from the literature review process and interaction with Industry experts. The questionnaire consists of 2 main parts; Part one is comprised of relevant demographic data showing age, years of practice, and type of firm. Part two comprised of 13item questions based on a 5-point Likert scale ranging from ‘strongly disagree (1), disagree (2), neither agree nor disagree (3). Agree (4), and strongly agree’ (5).

2.2. Study Population

The study population comprised of Pharmaceutical Sales Representatives from the six geopolitical zones (south-west-SW, south-south-SS, south-east-SE, north-central-NC, north-east-NE & north-westNW) in Nigeria.

2.3. Sample Size Determination

Sample size determination was based on respondents to item ratio of 10:1 as recommended for participants greater than 100. This will enable replicability of research (Izquierdo et al., 2014; Reio Jr & Shuck, 2015; Tabachnick & Fidell, 2007). In this study, 170 respondents answered a 13-item questionnaire with a greater than 13:1 ratio.

2.4. Sampling Design

The sample consists of 170 respondents (valid responses) out of 300 structured questionnaires administered to pharmaceutical sales representatives across the six geopolitical zones in Nigeria. . However, due to the absence of a reliable database, a purposive sampling method was used. The response rate was 75.6%.

2.5. Data Collection

The structured questionnaire contained 13-item Likert scale questions examining the perception of respondents about the relevance of work and work-related attributes during the period of lockdown in Nigeria which spanned from March 2020 to August 2020. 300 questionnaires in total were administered across the six geopolitical zones. Consent was obtained from respondents' through the provision of unique personal identifiers.

2.6. EPA Measures

The correlation Matrix considered values less than -0.8 or greater than 0.8. Value/s greater than 0.8 or below -0.8 imply that the value is an identity matrix, hence unacceptable. (See Appendix A). Communalities table accepts values equal and/or above 0.5 and rejects values below 0.5. Determinant values of the correlation matrix must be greater than 0.0001, to be considered significant/acceptable. An anti-image matrix was also determined (see Appendix B). Eigenvalues below 1 are considered unacceptable/redundant. Therefore, Eigenvalues greater than 1 are the preferred extraction criteria as shown in Figure 1. Eigenvalue measures the degree of variability of explanatory variables/factors accounted by a given factor. The total variance of factors must be equal to or greater than 50%. (Cokluk & Koçak, 2016; Cronbach, 1946; Debasish, 2004; Izquierdo et al., 2014).

2.7. Data Analysis Tools

Descriptive statistics such as Mean and Standard deviation SPSS version 23 was used to compute Factor analysis (FA) for the dataset. Two methods of factor extraction were deployed in this study; Principal component analysis (PCA) with varimax rotation and Principal Axis Factoring (PAF) with Promax rotation (Fabrigar, Wegener, MacCallum, & Straham, 1999; Henson et al., 2004; Kahn, 2006; Reio Jr & Shuck, 2015; Schreiber, 2020).

2.8. Factor Extraction Method and Factor Loadings Criteria

In this study, PCA and PAF were applied comparatively. PCA method presented simple representations of the structure of the latent variables (Mvududu & Sink, 2013; Nimon, Zigarmi, Houson, Witt, & Diehl, 2011). PAF was used to provide a more robust understanding of the latent structure of the observed variables under consideration (Henson et al., 2004; Treiblmaier & Filzmoser, 2010). Furthermore, this study interpreted variables as significant if they present factor loadings equal to or more than 0.5. (Debasish, 2004).

2.9. Test of Reliability and Validity

Cronbach alpha value of surveyed data was set at 0.7 baselines for internal reliability. Kaiser-MeyerOlkin (KMO) measure of sampling Adequacy was set at 0.5 baselines. KMO measure was set from the following criteria; a measure of >0.9=marvelous, >0.8=meritorious, >0.7=middling, >0.6=mediocre, >0.5=miserable and < 0.5=unacceptable. 0.5 is considered the absolute minimum validity value. KMO ensures that the distribution of observed values is satisfactorily adequate to conduct FA (Cronbach, 1946; Matsunaga, 2010; Tabachnick & Fidell, 2007).

2.9.1. Horn's Parallel Analysis (PA)

Horn's Parallel Analysis of the dataset (sample size=170, Number of items=13, 95th percentile with 1000 iterations) using SPSS syntax was used to determine factors to be retained (Horn, 1965; Ledesma & Valero-Mora, 2007; O'Connor, 2000). Parallel Analysis (PA) was applied by comparing Eigenvalues computed from actual data set with simulated dataset obtained from Parallel analysis (PA). When simulated Eigenvalues are greater than actual data Eigenvalues, the factor is removed and vice versa. (Cokluk & Koçak, 2016). (See PA output in Appendix C).

3. Results and Discussion

In this study, over 60% of respondents fell within the age bracket of 26 to 35 years as well as over 65% with below a year to 10 years of working experience in the pharmaceutical sales and marketing Industry. The minimum education level of respondents was first-degree polytechnic or University.

Table 1 shows the mean distribution of responses of respondents to the various items of the questionnaire; with the work-attributes (Q1-Enlightenment & Information provider) & (Q13Involvement in COVID screening) with the highest and lowest mean response scores respectively. Invariably, this implies that information & enlightenment about COVID disease and prevention had dominated the daily activities of PSRs. This is a sharp contrast from the norm in pharmaceutical sales and marketing operations, where firm-specific information dissemination activities geared to their product sales objectives are the practice (Elbeddini & Yeats, 2020; Gray et al., 2020). Conversely, the lowest score for item Q13 suggests that PSRs had little or no participation in actual COVID screening activities. This is an area to be explored by governments in developing countries where there is a paucity of trained and skilled first-line healthcare workers (Adeloye et al., 2017; Afriyie, Nyoni, & Ahmat, 2019). PSRs' can provide augmented services in this regard.

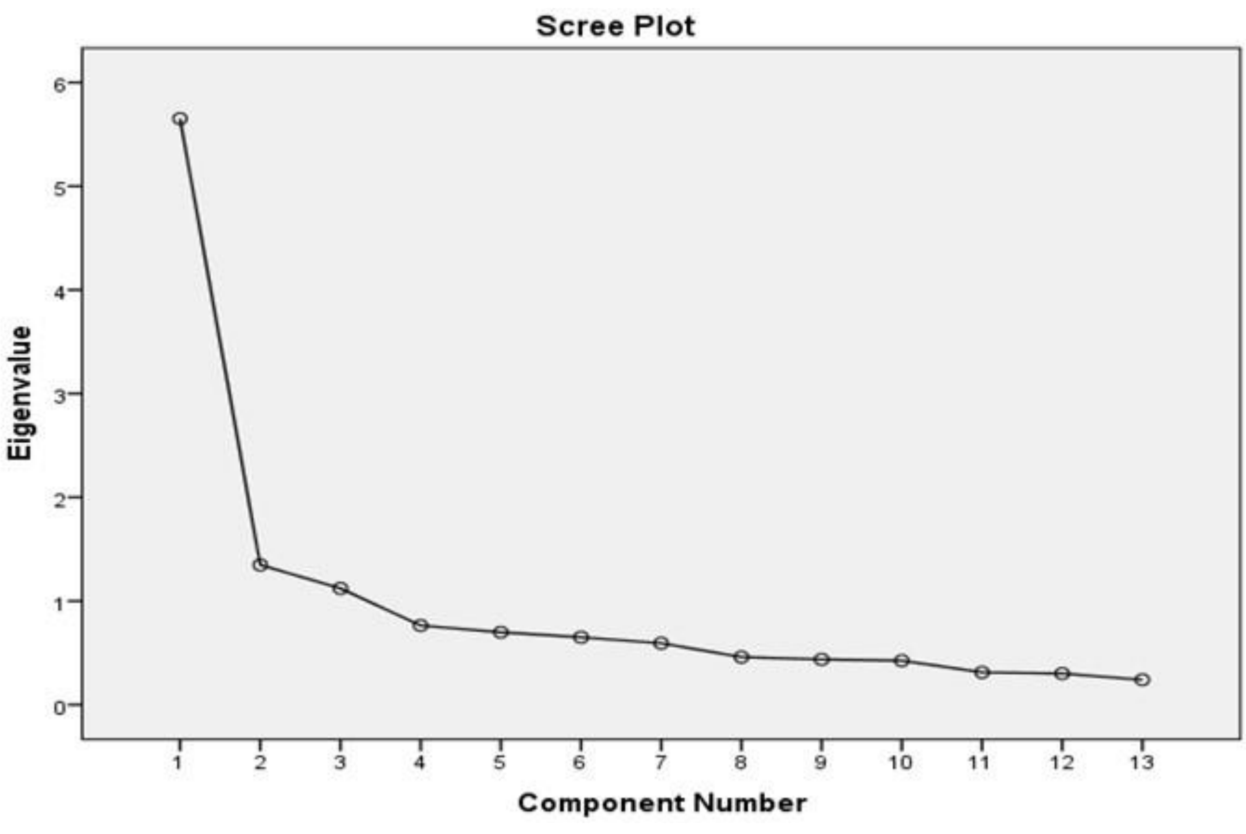

Figure-1.

Scree plot of Eigen values from dataset.

Table 2 shows that the measures of construct validity and adequacy were met by the dataset. In the same vein, the correlation matrix was found to satisfy the condition and hence confirms that correlation estimates of items were not due to chance. This provides a basis for the application of the factor analysis procedure as all pre-conditions have been fully satisfied. (See correlation matrix & anti-image matrix in Appendix A & B respectively).

Therefore, there is confirmed the construct validity of the dataset of the study and the results of exploratory factor analysis are valid, and therefore, the null hypothesis (**HO1)** was rejected.

In this study, as shown in Table 3, three (3) latent variables (Constructs) were derived from the factor extraction process; 1) Group 1: Sales-related activities, 2) Group 2: Communication/Accessrelated activities, and 3) Group 3: COVID-related activities. To achieve this, two-factor extraction methods were adopted; default Principal component analysis with orthogonal rotation (varimax) with the assumption that the factors are unrelated and Principal axis factoring with oblique rotation (Promax). Both methods produced similar output along the three constructs derived from the analysis.

Table-1.

Descriptive Statistics of Key Work Attributes of Pharmaceutical sales representatives during COVID-19 lockdown.

Items	Work Attributes of Pharma. Sales Representatives	Mean	Std. Deviation	Analysis N
Q1	Enlightenment & Information Provider	3.64	1.335	170
Q2	Received recognition/commendation for your sales efforts during the pandemic	3.07	1.357	170
Q3	Increased workload	3.13	1.498	170
Q4	Increased sales of your products	3.18	1.45	170
Q5	Involved in community education	2.85	1.404	170
Q6	Improved access to your customers	2.99	1.416	170
Q7	Limited access to your customers	2.95	1.516	170
Q8	Observed compliance by people during lockdown period	3.31	1.443	170
Q9	Enjoyed community appreciation of your efforts	2.86	1.443	170
Q10	Virtual consultation with clients/customers	3.26	1.404	170
Q11	Limited access to Doctors, nurses pharmacists (HCPs)	2.98	1.467	170
Q12	Made fresh contacts/new opportunities for business	3.09	1.477	170
Q13	Involved in COVID-19 screening activities	1.79	1.203	170

Table-2.

Exploratory Factor Analysis (EFA) Measures and Results.

Measures of Adequacy	Attribute	Threshold (cut-off values)	Study results	Inference
Kaiser=Meyer-Olkin (KMO)	A measure of sample adequacy of distribution	Marvelous >0.9, Unacceptable < 0.5	0.872	satisfactory

Bartlett's Test of Sphericity	A measure of multivariate normality	< 0.05	0.0001	satisfactory
Cronbach Alpha test of Internal reliability	A measure of internal reliability	criterion ≥ 0.7	0.888	satisfactory
Goodness of fit	Shows degree sample fits the population	significant value < 0.05	0.0001	satisfactory
Anti-Image Correlation	A measure of the correlation of items	between -0.8 and 0.8	> 0.5 but less than 0.8	satisfactory
Communalities	Extraction of factors	> 0.5	acceptable values ≥ 0.5	satisfactory
Non-redundant residuals	A measure of an identity matrix	< 0.05 (5%)	0.0003	satisfactory
Total Variance explained	A measure of variance by factors	> 50%	62.5	satisfactory

Note: Dataset satisfies all the criteria for construct validity. Hence, suitable for EFA.

Table-3.

Comparative Output Analysis of PAF and PCA Factor extraction Methods.

Factor extraction Method	**Items**	**Principal Component Analysis (PCA)**	**Factor loadings**	**Principal Axis Factoring (PAF)**	**Factor loadings**
Group 1	Q3	Increased workload	0.83	Increased Workload	0.932
	Q2	recognition for sales efforts	0.767	Recognition for sales efforts	0.771
	Q1	enlightenment & Information	0.686	enlightenment &Information	0.632
	Q4	Increased sales	0.537	Increased sales	0.615
	Q12	new contacts and opportunities	0.668		
Construct 1		Sales-related activities		Sales-related activities	
Group 2	Q11	limited access to HCPs	0.792	limited access to HCPs	0.843
	Q7	Virtual consultation	0.611	Virtual consultation	0.59

	Q8	Observed compliance	0.643	Observed compliance	0.621
	Q10	limited access to customers	0.757	limited access to customers	0.685
	Q9	community appreciation	0.508		
Construct II		Communication/Access-related activities		Communication/Access-related activities	
Group 3	Q13	COVID screening	0.859	COVID Screening	0.923
	Q5	Community education	0.707	Community education	0.561
	Q6	Improved access to customers	0.543		
Construct III		COVID-related activities		COVID-related activities	
No. of factors extracted		13		10	
Type of rotation		Varimax (orthogonal)		Promax (Oblique)	
Preferred Method		The principal axis factoring method (PAF) is preferred as it extracted items that best describe the constructs			

Group 1 with Sales-related activities had Q1, Q2, Q3, & Q4 in PCA & PAF. However, PAF excluded Q12 (made fresh contacts & opportunities for business). Similarly, the PAF technique also eliminated Q4 (community appreciation for efforts during COVID) and Q6 (improved access to customers) from Group 2 and 3 respectively. This was also premised on the fact that both attributes have been captured by other items in both groups. This exclusion by PAF is justified because the items/factors Q3- Increased workload & Q4-Increased product sales already presuppose by qualification that new opportunities/contacts for business were explored. At face value, PAF gave more precise parsimony of work-attributes in this group. Hence**, t**here is a consequential difference in the output of factor extraction methods; Principal component analysis (with varimax rotation) versus Principal axis factoring (with promax) method. Hence, the null hypothesis (**HO2**) was rejected. Furthermore, the implications of the output from PAF and PCA is supported by research studies that placed preference for PAF especially in datasets that may have inherent causal links or underlying theme or theory (Matsunaga, 2010; Mvududu & Sink, 2013). This strengthen the assertion by studies which showed that it gives more robust and accurate estimations of constructs (Dahling, Chau, Mayer, & Gregory, 2012; Kahn, 2006; Nimon et al., 2011; Tabachnick & Fidell, 2007)**.** Therefore, as shown in Table 4, this study preferred PAF method with promax rotation on four premises; a) constructs are well represented or captured by items/factors, b) PAF had relatively higher factor loadings compared to PCA method, c) has minimal repetition of similar or related items, d) 10 items summarized/represented compared to 13 items by PCA.

Table 4.

Pattern Matrix Output of PAF compared to Simulated Eigen Values from Parallel Analysis.

Items	**Key Work Attributes of Pharmaceutical sales representatives during COVID-19 lockdown**	**Component**			
		GROUP	**GROUP**	**GROUP**	**Communalities**

		1	**2**	**3**	
Q3	Increased work load	0.932			0.699
Q2	Received recognition/commendation for your sales efforts during the pandemic	0.771			0.641
Q1	Enlightenment & Information Provider	0.632			0.595
Q4	Increased sales of your products	0.615			0.582
Q12	Made fresh contacts/new opportunities for business				0.524
Q11	Limited access to Doctors, nurses & pharmacists (HCPs)		0.843		0.676
Q7	Limited access to your customers		0.685		0.604
Q8	Observed compliance by people during lock down period		0.621		0.593
Q10	Virtual consultation with clients/customers		0.590		0.671
Q9	Enjoyed community appreciation of your efforts				0.597
Q13	Involved in COVID-19 screening activities			0.923	0.747
Q5	Involved in community education			0.563	0.632
Q6	Improved access to your customers				0.559
EIGEN VALUE		5.651	1.348	1.122	
Simulated Eigen value (Parallel Analysis)		1.489	1.362	1.267	
PROPORTION OF VARIANCE accounted for by items or factors under component GROUPS		43.473	10.367	8.628	
CUMULATIVE VARIANCE		43.473	53.840	62.468	

Note: *Eigen applicable at values ≥1, factor loading cutoff- ≥0.5, Extraction Method: Principal Axis Factoring, Rotation Method: Varimax with Kaiser Normalization.

Table 5 presents an improvement on the initial solution presented in factor extraction and initial scree plot through the application of Parallel Analysis (PA) method (**see** Appendix C). Parallel analysis provided a rigorous and robust means to extract factors without the risk of overestimation of latent variables (Cokluk & Koçak, 2016; Ledesma & Valero-Mora, 2007; Matsunaga, 2010).

This analysis showed that only Group 1 had actual Eigen value greater than simulated Eigen value derived from PA SPSS syntax (**see** Appendix C). Groups 2 and 3 did not meet set criteria and hence were eliminated from the analysis. Consequently, there is significant difference between the actual Eigen values from dataset and simulated Eigen values output of Parallel Analysis (PA) and the null hypothesis **(HO3)** was rejected. Moreover, the final 4 observed variables or factors in Group 1 (one) presented with varied factor loadings; increased work load during the pandemic (0.932), received recognition/commendation for sales efforts during lockdown (0.771), enlightenment & information provider (0.631) and increased sales of products (0.615). The factor score ranking were shown to be Q3>Q2>Q1>Q4. It is suggested that 'increased work load' experienced by PSRs, was the work attribute with the highest relevance rating. Hence, the null hypothesis (**HO4)** was rejected.

Table 5.

Comparison between Study Eigen Values and Simulated Eigen Values.

Component	% of Variance	Study Eigen	Simulated Eigen	Decision
1	43.473	5.651	1.489	Accept
2	10.367	1.348	1.362	Reject
3	8.628	1.122	1.267	Reject
4	5.873	0.764	1.185	Reject
5	5.372	0.698	1.112	Reject
6	5.002	0.650	1.045	Reject
7	4.561	0.593	0.982	Reject
8	3.535	0.460	0.917	Reject
9	3.362	0.437	0.857	Reject
10	3.268	0.425	0.795	Reject
11	2.400	0.312	0.733	Reject
12	2.310	0.300	0.667	Reject
13	1.849	0.240	0.591	Reject

Note: Decision rule; remove components when simulated Eigen is greater than actual Eigen & vice-versa

4. Conclusion and Practice Implications

The strength of this study is that it puts in practice-perspective, the application of exploratory factor analysis in pharmaceutical sales and marketing research where knowledge, attitudes, practice, and perception-based questionnaires are often used for investigations. It is relevant to mention that the outcome of this study provides improved subjective thinking for pharmaceutical industry managers to explore appropriate constructs for phenomenon, sales process, marketing strategies and propound practice-based theories. Therefore, invariably to develop appropriate hypothesis or theory.

In addition, the parsimony effect achieved from factor analysis is very apt for middle and senior level managers who are inundated with large volume/s of data and information from which executive summaries are required for strategy formulation and implementation. This quantitative tool saves time, effort and impacts on the profitability of pharmaceutical firms and individuals.

On the policy level, as mentioned above, the use of exploratory factor analysis is significantly useful in informing decision making at the strategic, tactical, and operational levels of management in pharmaceutical sales and marketing companies, as it enables decision makers to identify, isolate the key issues/factors to be considered and the construct or context involved. This serves as a very informative strategy for filtering through large datasets, to relevant, manageable groupings with common characterization, in order to improve the quality, efficiency and generalizability of decisions. This tool finds application in research where content analysis is done as it ensures that critical/relevant data elements are fully considered.

5.1. Limitations of the Study

There were some limitations to this study, Limited sample size due to the unavailability of reliable database of pharmaceutical sales representatives in Nigeria. Although, sample size met criteria for use in exploratory factor analysis. Also, the number of questions in the questionnaire can also be increased with further literature search.

Abbreviations

Pharmaceutical sales representatives (PSR), Exploratory Factor Analysis (EFA), Principal Component Analysis (PCA), Principal Axis Factoring (PAF), Parallel analysis (PA),

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