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Research Article

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Identification of Factors Affecting Educational Performance of Nigerian Adult Learners: Exploratory Factor Analysis Approach

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Abstract The study identified the variables that tend to affect educational performance among adult learners. The population for the study consisted of students of Lagos State University, Ojo (Ilesa Study Centre). A sample of 1035 students was purposively selected from Modules IV and V students. Three research instruments were used for the study namely, a questionnaire and two inventories. Data collected was analyzed using multivariate statistical programme (factor analysis). The total variance explained by the initial eigenvalues using principal component analysis revealed eight factors (with eigenvalues greater than one) that accounted for almost 60 percent of the total scale variance. Seven factors were identified to affect educational performance. These were: Circumstances, Parental Authority, Socio-Economic Label, Self Concept, Training Environment, Health Characteristic and Socio-Economic Characteristic. These identified constructs shall be the basis for our further determination of the links among the various constructs, and also useful for gaining insight into the structure of our multivariate data.

Keywords Adult Learners, Correlation, Principal Components Extraction, Eigen-values, Extraction

Introduction

In many areas of psychology, sociology and education it is sometimes not possible to measure directly the concepts that are of major interest. Two obvious examples are intelligence and social class. In such cases, the researcher will often collect information on variables likely to be indicators of the concepts in question and then try to discover whether the relationships between these observed variables are consistent with them, being measures of a single underlying latent variable, or whether some more complex structure has to be postulated.

In such studies, the most frequently used method of analysis is some form of *factor analysis*, a term which subsumes a fairly large variety of procedures, all of which have the aim of ascertaining whether the interrelations between a set of observed variables are explicable in terms of a small number of underlying, unobservable variables or *factors*. For example, reference [1] tested several confirmatory factor analytic models to describe the relationships among 25 measured variables related to meaning and satisfaction in life.

Basic Factor Analysis Model

Factor analysis is concerned with whether the covariances or correlations between a set of observed variables, $x' = \lfloor x_1, ..., x_p \rfloor$, can be 'explained' in terms of a smaller number of unobservable, latent variables $f_1, \ldots, f_k$ where $k < p$. Explanation in this case means that the correlation between each pair of observed variables results from their mutual association with the latent variables; consequently, the *partial* correlations between any pair of observed variables, given the values of $f_1, \ldots, f_k$, should be approximately zero. The simplest model that satisfies the requirement that the observed variables are conditionally uncorrelated, given the values of all f_i, is the following:

$$\begin{aligned} x_1 &= \lambda_{11} f_1 + \lambda_{12} f_2 + \lambda_{13} f_3 + \ldots + \lambda_{1k} f_k + u_1, \\ x_2 &= \lambda_{21} f_1 + \lambda_{22} f_2 + \lambda_{23} f_3 + \ldots + \lambda_{2k} f_k + u_2, \\ &. \\ &. \\ &. \\ x_p &= \lambda_{p1} f_1 + \lambda_{p2} f_2 + \lambda_{p3} f_3 + \ldots + \lambda_{pk} f_k + u_p, \end{aligned} \tag{1}$$

or written more concisely

$$x = \Lambda f + u, \tag{2}$$

where $$\Lambda = \begin{pmatrix} \lambda_{11} & . & . & . & \lambda_{1k} \\ . & & & & . \\ . & & & & . \\ . & & & & . \\ \lambda_{p1} & . & . & . & \lambda_{pk} \end{pmatrix},$$

and $$f = \begin{pmatrix} \mathrm{f}_1 \\ . \\ . \\ . \\ \mathrm{f}_k \end{pmatrix},$$

and $$u = \begin{pmatrix} \mathrm{u}_1 \\ . \\ . \\ . \\ \mathrm{u}_p \end{pmatrix},$$ and **u** is the vector error.

Materials and Methods

The population for the study consisted of students of Lagos State University, Ojo (Ilesa Study Centre). A sample of 1035 students was purposively selected from Modules IV and V students out of a total number of 2248 students in Modules II to V. In determining this sample size (n), a simple appropriate sample estimation was used;

$$n = p(1-p)\left(\frac{Z_\alpha}{d}\right)^2, \tag{3}$$

where p = proportion or a best guess about the value of the proportion of interest;
d = the tolerance (distance) level effects i.e. how close to the proportion of interest the estimate is desired to be (e.g. within 0.05); and

$1-\alpha$ = the confidence level that our estimate is within distance (d) of the proportion of interest [$\alpha = 1 - confidence$ level].

In carrying out this study, data were collected through structured instruments (a questionnaire and two inventories) representing all the adult learners in all the sandwich degree programmes in Nigeria through generalization [2-3]. In order to screen the variables that have positive or negative effects on educational performance based on data collected, we employed the use of multivariate statistical programme (factor analysis) for construct identification.

Results and Discussion

Adequacy of Extraction and Number of Factors

Because inclusion of more factors in a solution improves the fit between observed and reproduced correlation matrices, adequacy of extraction is tied to number of factors. The more factors extracted, the better the fit and the greater the percent of variance in the data "explained" by the factor solution. However, the more factors extracted, the less parsimonious the solution.

There are several ways to assess adequacy of extraction and number of factors.

A first quick estimate of the number of factors is obtained from the scree test of eigenvalues plotted against factors. Factors, in descending order, are arranged along the abscissa with eigenvalues as the ordinate (See Figure 1). The scree plot is decreasing – the eigenvalue is highest for the first factor and moderate but decreasing for the next few factors before reaching small values for the last several factors. The point where a line drawn through the points changes slope is considered. From Figure 1, a straight line can comfortably fit the first eight eigenvalues. After that, another line, with a noticeably different slope, best fits the remaining twelve points. Therefore, there appear to be about eight factors in the data of Figure 1.

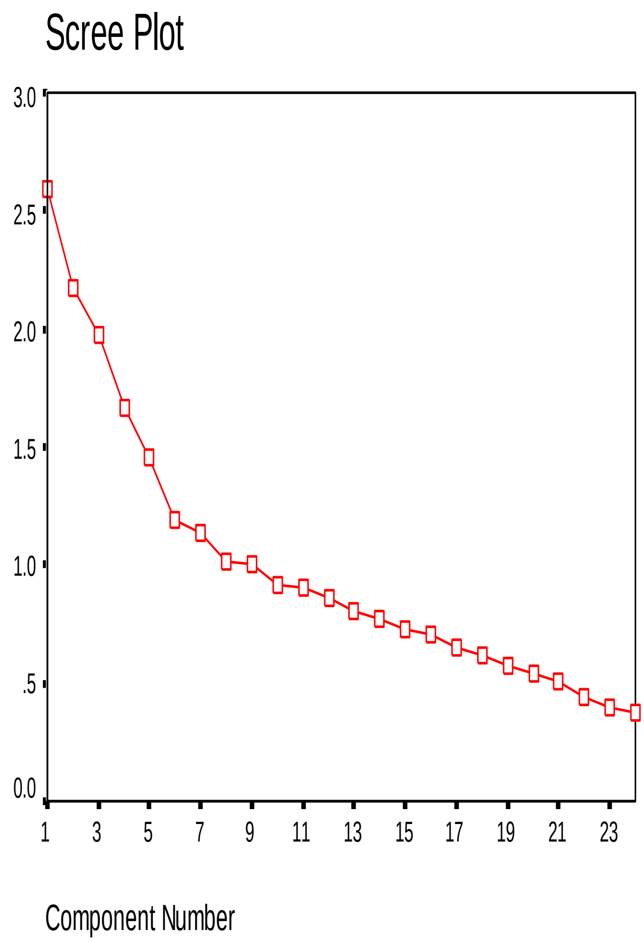

Figure 1: Sreee Plot for Factor Identification

A second criterion is obtained from the sizes of the eigenvalues reported as part of an initial run with principal components extraction in Table 1.

Table 1: Total Variance Explained by the Initial Eigenvalues of the Factors

Factor	Eigenvalue	% of Variance	Cumulative %
1	2.594	10.810	10.810
2	2.170	9.041	19.851
3	1.969	8.203	28.054
4	1.665	6.936	34.990
5	1.453	6.056	41.046

6	1.194	4.974	46.020
7	1.134	4.724	50.744
8	1.020	4.250	54.994
9	1.000	4.166	59.160
10	.918	3.825	62.985
11	.900	3.750	66.735
12	.863	3.594	70.329
13	.811	3.377	73.707
14	.767	3.196	76.903
15	.732	3.048	79.951
16	.705	2.937	82.888
17	.648	2.698	85.586
18	.617	2.572	88.159
19	.574	2.392	90.550
20	.544	2.267	92.817
21	.508	2.116	94.933
22	.441	1.840	96.772
23	.397	1.655	98.427
24	.377	1.573	100.000

Eigenvalues represent variances. Because the variance that each standardized variable contributes to a principal components extraction is one, a component with an eigenvalue less than one is not as important, from a variance perspective, as an observed variable. The number of components with eigenvalues greater than one is usually somewhere between the number of variables divided by three and the number of variables divided by five (for example 24 variables should produce between eight and five components with eigenvalues greater than one). Therefore, there appear to be eight components in the data of Table 1.

From the two ways of assessing adequacy of extraction above, there seems to be eight factors in the data, hence there is need for construct identification from the 24 variables.

Construct Identification

From Table 2, the variations in the data accounted for by the factors vary from 9.840 for Factor 1 to 4.417 for Factor 8. The variations are so close especially for the first four factors (9.840, 8.850, 7.473 and 7.358) confirm that not just one factor may be responsible for the variation in the definition.

Table 2: Factor Loadings for Construct Identification

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 5**	**Factor 6**	**Factor 7**	**Factor 8**	**Communality**
DISSAPP	**.764**	-	-	-	-	-	-	-	0.598
TRAVES	**.640**	-	-	-	-	-	-	-	0.455
REJECT	**.601**	-	-	.279	-	-	-	-	0.460
THREAT	**.590**	-	-	-	-	-	-	-	0.399
LOSS	**.573**	-	-	-	-	.251	-	-	0.437
FEAR	**.457**	-	-	-	-	-	-	-	0.404
AURITIVE	-	**.849**	-	-	-	-	-	-	0.732
AUTHORIAN	-	**.819**	-	-	-	-	-	-	0.720
PERMISS	-	**.782**	-	-	-	-	-	-	0.691
AGE	-	-	**.832**	-	-	-	-	-	0.718
MARSTATUS	-	-	**.730**	-	-	-	.270	-	0.663
EDULEVEL	-	-	**.529**	-	-	-	-	-	0.327
SELFDES	-	-	-	**.765**	-	-	-	-	0.639
SELFCRIT	-	-	-	**.632**	-	-	-	-	0.429
APTITUDE	-	-	-	**.545**	-	-	-	-	0.334
BOARDFAC	-	-	-	-	**.803**	-	-	-	0.659
KINDSCH	-	-	-	-	**.789**	-	-	-	0.645
HSPTABEF	-	-	-	-	-	**.693**	-	-	0.589
AFECTDIS	-	-	-	-	-	**.638**	-	.258	0.561

TYPEMAR	-	-	-	-	-	-	**.657**	-	0.495
RELIG	-	-	-	-	-	-	**.528**	-.265	0.541
OCCUP	-	-	-.401	-	-	-	**.460**	-	0.433
GENDER	-	-	-	.405	-	-	**.421**	-	0.493
GPA	-	-	-	-	-	-	-	**.856**	0.775
Eigenvalue	2.361	2.124	1.794	1.766	1.393	1.360	1.341	1.060	
% Variance	9.840	8.850	7.473	7.358	5.803	5.666	5.586	4.417	
Possible Construct	Circum-Stance	Parental Authority	Socio-Economic Label	Self Concept	Training Environ-ment	Health Xteristic	Socio-Economic Xteristic	Educ. Perfor-mance	

* *Bolden values are indicative of correlated factors*

In particular, Factor 1 has high positive loadings for *disapp*, *traves*, *threat*, *loss* and *reject*, moderate positive for *fear* which measures the extent of ill things or circumstances that ocurred to a learner. Factor 2 has high positive loadings for *auritive, auhorian* and *permiss*. This can be labelled "parental authority" of a learner.

Furthermore, Factor 3 has high positive loadings for *age, marstatu* and *edulevel*. It therefore measures the extent of socio-economic label of an adult learner. Factor 4 has high positive loadings for *selfdes, selfcrit* and *aptitude.* It therefore measures the extent of self concept of a learner.

Moreso, Factor 5 has high positive loadings for *kindsch* and *boardfac* and can be labelled "training environment" of an adult learner. Factor 6 has high positive loadings for *hsptabef* and *afectdis*, which measures the extent of health characteristic of a learner.

Conclusively, Factor 7 has high positive loadings *typemar* and *relig,* moderate positive loadings for *occup* and *gender* which measures the extent of socio-economic characteristic of an adult learner. Factor 8 has positive loading for *gpa*. It therefore measures the extent of educational performance of a learner.

Conclusion

The total variance explained by the initial eigenvalues using principal component analysis revealed eight factors (with eigenvalues greater than one) that accounted for almost 60 percent of the total scale variance. The identified eight factors were: Circumstances, Parental Authority, Socio-Economic Label, Self Concept, Training Environment, Health Characteristic, Socio-Economic Characteristic and Educational Performance. This identification shall be the basis for our further determination of the links among the various constructs. We have also found this result of factor analysis useful for gaining insight into the structure of our multivariate data.

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