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An Application of Factor Analysis to Identify the Most Effective Reasons that University Students Hate to Read Books

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Factor analysis (FA) is a method of location for the structural anomalies of a communality consisting of p-variables and a huge numbers of values and sample size. It cuts the value of original variables by finding a minor value of the latest variables that are known as factors. In this study, a principal components analysis (PCA) will be applied to summarise the factor analysis and their application by estimating the factors with Varimax rotation and using the SPSS statistic package. The application is survey based using 462 random undergraduate candidates aged between 17 to 33 years old at Salahaddin University-Erbil. The most significant effect in this phenomenon was shown as a poor level of book contents, cost of books, unknown other languages, and lack of basic facilities including water and electricity respectively.

Key words: *Factorial analysis, Principal components analysis, students don’t read books.*

Introduction

Reading is one of the most important skills when learning a language. Reading is defined as a two way interaction in which the learner and the writer share knowledge between themselves (Brunan, W.K., 1989). The word "read" is accepted as making sense of written or printed text or symbols (Oxford South African Dictionary, 1973). On the other hand, reading is defined as the act of communication in which information is transferred from a transmitter to a receiver.

There are many reasons that people do not like to read a random book that takes time, such as, no free time, no financial aid, don't have experience, no mood, too difficult to understand, or it is just not a habit (Lombardi, 2017; Ihtiyaroglu, and Ates, 2018). Numerous individuals and their family members mentioned that the amount of money to pay for school is heavy on its own. Other studies show that 7 in 10 candidates mentioned that they never even buy a reference book once as they cannot afford it (Redden, 2011). In this study, the sample group are1905 undergraduate students from 13 schools, involving both universities and colleges from government sectors. About 78% of the candidates who never had a book were not confident about receiving a good grade in that class (Redden, 2011). Many lecturers maintain the habit of inspiring students to read books, stories or novels, besides the academic texts set (Wambach, 1999). However, other staff never care to engage the students to read, because they worry that the students might evaluate them badly (Sappington *et al.,* 2002). In the same respect, Clump, Bauer and Bradley (2004) discovered during psychology classes that reading rate is higher compared to other classes. Poor reading rates by the students was noted due to the large numbers of students who read only to get a higher mark and not with the aim of educating themselves (Ryan, 2006).

In addition, the National Endowment of the Arts report (2007) reinforces Nathan's report that candidates interface with social media and media devices much more than with books for the aim of reading. The ability to read well does not depend on the methodological book that offers the minimum of information, but students should use assistive books or other sources from libraries to expand the demand for knowledge (Bond, 1960). In other words, the candidates who keep mentioning that they don't like to read are those who believe that they will never be able to read (Wigfield, Eccles, and Rodgriguez, 1998) even if they do their best (Zimmerman, 2000). Many university professors reported that candidates who finish reading their homework are those who contribute more in the classroom (Lei, 2010, Sappington *et al*., 2002) and their discussions are always valuable and useful (Ruscio, 2001) besides that, their overall social skills improve (Burchfield and Sappington, 2000; Karp and Yoels, 1976).

Methods & Material

The goal of this research is to find the most prevalent reasons why university students do not like to read books. The data was collected using a questionnaire format of 462 random undergraduate students (242 men and 220 women) who were non-compliant with reading books at University of Salahaddin-Erbil. This survey form contains two parts. The initial part is a set of demographic questions which include gender, age, and place of residence, economic status, marital status, and father's and mother's education. The second part was about the reasons for lack of reading books. A Likert scale (not reason at all=1, not reason=2, neutral=3, reason=4, reason at all=5) was administrated in this study. The researchers initially completed a pilot study of 20 cases to make sure ofthe validity of questionnaires, and also they used the Kronbach's Alpha (0.89) to test the consistency of the data. Furthermore, Factor Analysis was utilised to choose the most prevalent reasons for lack of reading books.

Results and Discussion

Descriptive Statistics

Table 1: Descriptive Statistics for qualitative variables.

Categorical Variables		**F**	**%**
Gender	Male	242	52.38%
	Female	220	47.62%
Place of resident	Urban	238	51.52%
	Rural	224	48.48%
Stages of study	Intial Stage	122	26.41%
	Second Stage	84	18.18%
	Third Stage	113	24.46%
	Fourth Stage	143	30.95%
Economics Status	Very good	29	6.28%
	Good	209	45.24%
	Medium	158	34.20%
	Bad	66	14.29%
Marital Status	Married	67	14.50%
	Single	395	85.50%
Father Educated background	Illiterate	74	16.02%
	Primary	145	31.39%
	Secondary	123	26.62%
	Diploma	46	9.96%
	Collage	31	6.71%
	Master	35	7.58%
	More than Master	8	1.73%
Mother Educated background	Illiterate	186	40.26%
	Primary	155	33.55%
	Secondary	53	11.47%

	Diploma	28	6.06%
	Collage	23	4.98%
	Master	14	3.03%
	More than Master	3	0.65%

Table (1) shows that the most of the students in this survey are male (52.38%) and single (85.50%) in the fourth grade (30.95%). In other hand, they live in an urban setting (51.52%) and have a good economy (45.2%). Unfortunately, most student's mother's education reflect that they are illiterate (40.26%).while their father's education is generally of primary level (31.39%).

Factor Analysis (FA)

A multivariate statistical class helps to reduce and summarize data. This has the ability to handle the analysis and interrelationship of huge numbers of variables following the explanation of these variables in terms of their common as well as underlying factors. This statistical method is part of principal component (PCA) technique, whereby the outcome and the clarification in these steps are alike, however the mathematical models are diverse. In addition, this method correlates a huge numbers of quantitative variables. It decreases the value of original variables by looking at a smaller number of the latest variables to be named as factors. When grouping variables into factors the reduction would be activated as each variable in every single factor is nearly related whereas, variables of various factors are less related (Johnson and Wichern, 2013; Blbas, *et al*. 2017).

Factor analysis has a unique feature which makes it very different from other procedures in separate documentation in dependent or independent variables is absent. Therefore, the link among variables is tested deprived of the requirement of each variable following the other. Thus, factor analysis does not require multivariate normality in all extraction techniques (Tabachnick and Fidell, 2001; Irida and Rina, 2017).

Sample Size

The least possible required sample size based on McQuitty (2004) is to calculate and identify the number in advance of the data collection. In order to reach the required statistical value in a specific model, a defined answer consists of stable variables and reduces the effect of sample size; , a greater numbers of research subjects reduces sampling error and gives rise to more stable alternatives (Hogarty *et al*., 2005). Numerous of scientists have suggested various strategies in order to find the sample size as presented through table (2).

Table 2: Required sample size for analyzing Factor Analysis

Author's Name	**Sample Size**
Guilford (1954)	At least 200 cases.
Lawley and Maxwell (1971)	Number is 51 cases greater than the variables.
Cattell (1978)	Based on Variable ratio from 3:1- 6:1. The least possible sample size is 250.
Gorsuch (1983) and Kline (1979)	At least 100, despite the number of variables.
Gorsuch (1983)	At least 200 cases, regardless of STV.
Comrey and Lee (1992)	Suggest to find 500 or more sample size whenever is applicable.
Hatcher (1994)	Sample size to be 5 times greater than the variables.
Hair, Anderson, Tatham, and Black (1995)	Should be twenty folds bigger than the value of variables (Ratio of 20:1).
Bryant and Yarnold (1995)	10 cases in each portion, and the subject-to-variable rate is not lesser than 5.
Hutcheson and Sofroniou (1999)	150 - 300 cases and 150 cases for the strongly correlated variables.
Norušis (2005)	At least 300 cases
Suhr (2006).	100 cases and a STV ratio should be no fewer than five
Garson David (2008)	10 cases for each portion.

Depending on the rules as detailed in table 2, the number of sample size of Factor Analysis is satisfying, because the value of sample size in this survey is 642 with 18 items and subject to variables is (26:1).

Evaluating Communalities

Forms the part of the variance in the initial variables which is calculated by the factor solution which is defined as 50% of the said variable's variance, therefore the amount for every variable is somehow 0.50 or greater.

Table 3: Represents the Communalities of variables.

Variables (In your point of view, the following points and questions are reasons for lack of reading)	Extraction (Iteration 1)	Extraction (Iteration 6)
X1 (Students feel that reading is not useful)	0.523	0.794
X2 (I spent too much time watching films and programs on TV)	0.674	0.696

X3 (Lack of interesting and motivation to read books)	0.437	
X4 (Economic issues impose students to work)	0.403	
X5 (Students' preoccupation with using technology including internet and mobile)	0.418	
X6 (Students' attention on academic study and achievement at university)	0.421	
X7 (Lack book fairs at college and university)	0.569	0.544
X8 (Absent of suitable library at university and college)	0.647	0.615
X9 (Lack of book readers who reinforce and motivate reading books)	0.476	
X10 (Deficiency in reading culture from childhood which required to be taught by parents)	0.604	0.693
X11 (Familiarizing children with reading culture by teachers at the primary grades)	0.563	0.659
X12 (Level of parents' education)	0.727	0.521
X13 (Social political issues)	0.408	
X14 (Lack of basic facilities including water, electricity, etc.)	0.631	0.557
X15 (Lack of time for reading)	0.474	0.553
X16 (Poor level of book contents)	0.431	0.522
X17 (Cost of books)	0.605	0.599
X18 (Lack of Knowledge of other languages)	0.661	0.559

In the first iteration, there are actually EIGHT variables that have communalities less than 0.50 in table 3. The variable with the smallest communality is selected for removal which is the communality for the variable (X4 = 0.403).The variable X4 is excluded and then the principal component analysis was computed one more time. In this relation, after deleting X4, there are still five variables that have communalities less than 0.50. The variables with the smallest communality (X6, X3, X5, X13, and X9) consequently are selected for removal.
After deleting six variables, the communalities in all other variables involves the portions higher than 0.50 and satisfies the requirement of Factor Analysis.

Evaluate Factorability of Matrices

Correlational is another assumption of Factor Analysis, the strength of linear relationships is calculated via the correlation matrix formed after the data. In fact, the correlation values greater than 0.30 provide evidence of sufficient unity to defend comprising factors (Tabachnick and Fidell, 2001). In cases when the inter-correlations are somehow poor, it could be due to poor variance. Furthermore, data that are homogenous represent poor variance (Fabrigar *et al.*, 1999).

Table 4: Represents the Correlation Matrix of TWELVE Items for the University Students do not like to Read the Book (USHRB).

Table 4: Represents the Correlation Matrix of the USHRB.

		x2	x7	x8	x10	x11	x12	x14	x15	x16	x17	x18
Correlation	x1	.175	.061	-.019	.121	.148	.028	.043	.065	.031	.031	.018
	x2		.007	.054	.104	.106	-.024	-.138	-.093	.011	.042	.065
	x7			**.390**	.141	.226	-.014	.127	.183	.209	.255	.095
	x8				.163	.247	-.022	.070	.229	.197	.186	.122
	x10					**.432**	.147	.033	.062	.072	.077	.175
	x11						.026	.134	.091	.064	.123	.170
	x12							.125	.019	.146	.103	.094
	x14								.274	.278	.190	.175
	x15									.290	.218	.093
	x16										**.334**	.192
	x17											**.324**

- The readings in red are greater than 0.30.

In these values, there are 4 correlations in the matrix bigger than 0.30, which fulfills their needs (Table 4).

Kaiser-Meyer-Olkin (KMO) and Bartlett's test

A- Kaiser-Meyer-Olkin Test of Sampling Adequacy

These tests are a measurement of the item's mutual variance.
The following guidelines for evaluating the measure are suggested by Kaiser, Meyer and Olki n (Friel, n.d.):

Table 5: Represents the Interpretation Guidelines for Kaiser-Meyer-Olkin (KMO).

KMO Value	Degree of Common Variance
0.90 - 1.00	Marvelous
0.80 - 0.89	Meritorious
0.70 - 0.79	Middling
0.60 - 0.69	Mediocre
0.50 - 0.59	Miserable
0.00 - 0.49	Don't Factor

B- Bartlett's Test of Sphericity

This test is used when the number in the USHRB is near to zero. Bartlett's test's null hypothesis shows that the known correlation matrix is equivalent to the identity matrix, indicating that the showing matrix is not factorable (Pett *et al*., 2003). Principal component analysis requirements are possibly related to the Bartlett's Test of Sphericity and were fewer than the value of significance. In this example from iteration 6, Bartlett's Test result in table 6 proves that the correlation matrix is statistically varied from a singular matrix and shows that linear combinations exist.

Table 6: KMO and Bartlett's Test.

		Iteration 1	Iteration 6
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.744	0.695
Bartlett's Test of Sphericity	Approx. Chi-Square	1097.143	605.314
	df	153	66
	Sig.	0.0001	0.0001

According to the results in table 6, all measurements of Sampling Adequacy (MSA) were 0.86 in the rest of factors, which has been gone beyond the basic requirement of 0.50. The further 12 variables form the foundation needed in factor analysis.

Initial Extraction

The factoring starts with the initial extraction of linear combinations. The linear combinations of items made by the matrix algebra are then used to highlight the highest amount of variance 1 among the others. It adopts every combination as orthogonal for each uncorrelated element, which are called factors or sometimes known as components. The original factor highlights the highest proportion for different elements. However, the following combination acts to target the largest sum for the rest. This method is carried out until every single factor in the pool is highlighted (Suhr, 2006).

Process of Initial Extraction

Principal Component Analysis (PCA) includes all the factors in the preliminary extraction. It is the commonly applied extraction technique in component analysis as well as for reducing the values in each portion into a minimal value of each components (Costello and Osborne, 2005; DeCoster, 1998). The known factor analysis only consists of the shared variance in the extraction. Principal Axis Factoring (PAF) and Maximum Likelihood Estimation (ML) are the two most common extraction techniques of common factor analysis. PAF doesn't involve distributional assumptions and it could be applied for values which are not normally distributed (Fabrigar et al., 1999), while ML needs multivariate normality (Pett et al., 2003).

Determine the Number of Factors to Retain

According to the outcome from the initial extraction, the practitioner has got to decide the number of factors that ought to be maintained to best present the value and the current links. The most variance is due to the first factor and the values of variance shown by using every subsequent factor continually reduces (Tabachnick & Fidell, 2001).
The aim is to pick up sufficient factors to adequately show the value, when removing the factors that are not statistically related (Fabrigar et al., 1999).

A- Kaiser Criterion

This is the most commonly used eigenvalue criteria (Costello & Osborne, 2005).
Kaiser Criterion only applied in PCA once the sum of variance is found to be in the extraction (Pett et al. 2003).

Table 7: Shows the Sum of Variance Explained for a Principal Component Analysis of the USHRB.

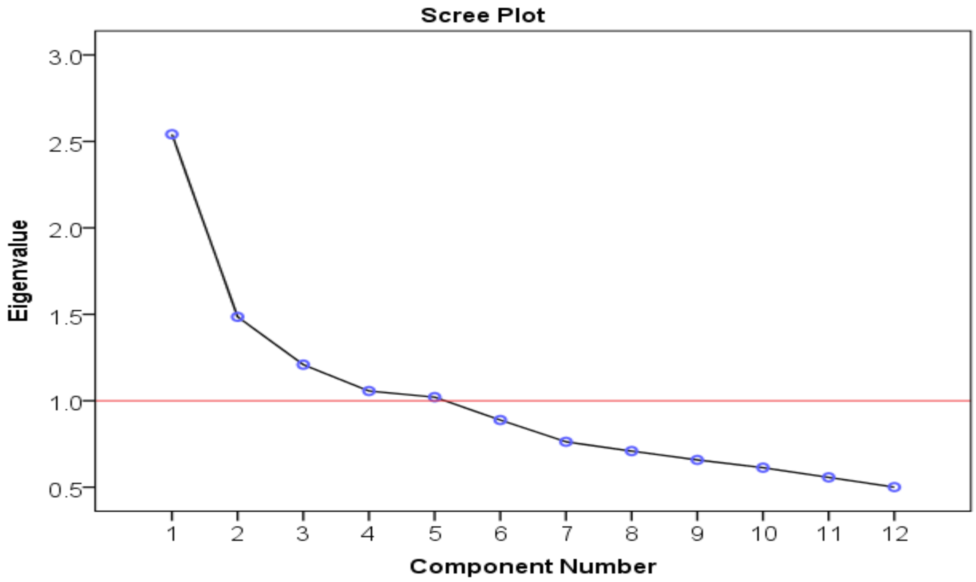
Component	Initial Eigenvalues			Rotation Totals of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.541	21.177	21.177	1.574	13.118	13.118
2	1.485	12.377	33.554	1.570	13.084	26.202
3	1.209	10.073	43.627	1.530	12.748	38.950
4	1.056	8.804	52.431	1.476	12.299	51.249
5	1.021	8.507	60.938	1.163	9.689	60.938

Table 7 represents the total percentages of variance criteria which needs 5 portions to fulfil the requirements in 60% or more of the sum variance. In this example, five factors have to be gained to efficiently represent the USHRB rate which explains 60.938% of the total variance by using the Kaiser Criterion.

B- Scree Plot

This is a graphical illustration which consist of factors and their corresponding eigenvalues. Because the greatest value of variance is calculated by the first component, it contains the largest eigenvalue, which gradually reduces the outcome in a graph which is known as the "elbow" shape. The cut off of scree plot is rather subjective as it needs the value of factors to be related to the occurring prior to the bend in the elbow (Fabrigar et al., 1999).

Figure 1. Represents the scree plot of the eigenvalues and factors from the USHRB extraction.



C- Variance Extracted

This determination technique according to a similar conceptual framework is to maintain the value of factors that account for a specific percentage of the origin variance.

The related works varies on the numbers of variance and should be clarified prior to the value of factors as adequate. Mostly, seventy five to ninety percent of the variance needs to be calculated (Garson, 2010; Pett et al., 2003); numerous researchers validate that fifty percent of the variance explained is acceptable. It is better to consider the first extraction with various criterion steps and through associating the factors advised to be kept (Costello & Osborne, 2005; Schonrock-Adema et al., 2009). From an example, five factors should be retaining bases on the three criteria such as the eigenvalues, the scree plot, and the proportion of variance extracted. It is possible to exercise various number of factors booked and compare the solutions (Table 7).

Factor Rotation

When performing a factor analysis, factor rotation is easily recognized as a consecutive step. As mentioned above, these relationships are linear combinations of the factors as well as the factor loadings which are all variable. The mathematical aim of factor analysis is to summarize the relationship among variables and the factors. There is no single or unique solution of these linear combinations (Fabrigar et al., 1999). All other factors ought to be thrown out once the number of factors to include has been set. The items are factored one more time then it is compulsory to have to specify number of factors. That solution is then rotated to create the factor rotation as the literature indicates that rotating the initial factor solution is critical to the factors and indicator variables interpretation. Tabachnick and Fidell (2001) showed that no extraction strategies routinely supply an interpretable solution without rotation as well as (Fabrigar at el., 1999) stating that it is essential for a scientist to pick out process for rotating the preliminary factor analytic solution to a latest solution.

Orthogonal and Oblique Rotations

These rotations are known as the key point in rotation method. First of all, orthogonal rotations (varimax, quartimax, and equimax) are acceptable only for the aim of factor analysis to develop factor scores (PCA) or as cases once the theoretical hypotheses concern unrelated dimensions (Loo, 1979). Varimax is mostly considered best and is most generally used in the orthogonal rotations, (Fabrigar et al., 1999; Loo, 1979). Secondly, oblique rotations account for the relationships among the factors that frequently are further acceptable within social science studies. Fabrigar et al. (1999) shows that oblique rotations are applied when factors were not correlated, then an assumption of factors which are near to zero will be released by the rotation. An oblique rotational method includes Direct Oblimin, Promax, Orthoblique and Procrustes. There is never one greatest technique for oblique rotations, therefore this technique selection must always be based on the choices presented by the software system (DeCoster, 1998; Fabrigar et al., 1999).

Identifying Simple Structure

It is established once every factor is illustrated by multiple portions that each variable can only load on it one factor (Pett et al., 2003; Tabachnick & Fidell, 2001). Essentially, an item is identified as a decent factor identifier of the factor if the loading is 0.70 or higher and does not significantly cross load on another factor bigger than .40 (Garson, 2010). Tabachnick and Fidell (2001) suggest that the secondary loading ought to be no greater than 0.32. Costello and Osborne (2005) pose that a loading of 0.50 is enough to be considered “strong,” whereas Guadagnoli and Velicer (1988) state that the loading should be 0.60 or higher. On iteration 6, it was not a must to delete any extra variables as none of the variables demonstrated complex structure. After removing variables according to low communalities and complex structure, the factor solution is examined to get rid of any components that have only a single variable loading on them. If a component has only a single variable loading on it, the variable must be excluded from the next iteration of the principal analysis. On iteration 6, the five components in the analysis had over one variable loading for each factor.

Table 8: Shows the Rotated Component Matrix[a] for a Principal Component Analysis of the USHRB.

Variables	Component				
	1	2	3	4	5
x18	0.716				
x17	0.715				
x16	0.512				
x14		0.716			
x15		0.670			
x10			0.824		
x11			0.756		
x8				0.724	
x7				0.674	
x12				-0.498	
x1					0.835
x2					0.638
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 6 iterations.					

Conclusions

Based on the correlations among the great values of qualitative variables, factor analysis (FA) is used to reduce the value of the initial variables by finding a reduced value of latest variables to be known as factors. Note for the first component which is a great significance in the interpretation of the reasons for not reading (13.12%) of the total variance is explained as it has a set of variables affecting the phenomenon such as poor level of book contents (X16), cost of books (X17), and unknown other languages (X18) respectively.

For the second component where (13.08%) of the total variance is explained, there is a set of variables affecting the phenomenon such as absence of basic services like water, electricity, etc. (X14) and lack of time for reading (X15) respectively. The component records (12.75%) of the total variance and has a set of variables affecting the phenomenon like deficiency in reading culture from childhood which was required to be taught by parents (X10) and familiarizing children with reading culture by teachers in the primary grades (X11) respectively.

The fourth component represents (12.29%) of the total variance and has a set of variables affecting the phenomenon like lack book fairs at college and university (X7), absence of suitable library at university and college (X8), and level of parents' education (X12) respectively. Finally, the fifth component which explains (9.69%) of the total variance has a set of variables affecting the phenomenon such as students feeingl that reading is not useful (X1) and that they spend too much time watching films and programs on TV respectively.

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