# Using factor model to study the crime in South Darfur State

## Paper prepared by:

- 1. Dr. Abdelgalal Osman Idris Abaker<sup>1</sup>
- 2. Dr. Mohammed Ahmed Nour Ali<sup>2</sup>

#### Abstract

This research is an implementation of the factor analysis model on criminal activities in South Darfur State. The problem is: are there any unobserved variables (factors) in the field of crime in the State, what is the underlying structure of the crime in South Darfur State, and to what extent are the variables associated with crime can be reduced. The aims of the study are to study the underlying structure of the crime in South Darfur State and to know to what extent that the data of the crime could be reduced. The population of the study is the people who are involved in different criminal activities. The sample size is 667 persons. The data was collected using quota sampling. An analytic procedure was used to analyze the data using SPSS by factor analysis. The correlation matrix was analyzed to perform factor analysis; principal component was selected for extraction and varimax for rotation. After the literature was reviewed and the data was analyzed, the researcher discusses the results of analysis and comes to acceptable results as follows: Seven factors were extracted to explain 64.23% of the total variance of the crime in the State. The most important factors are the punishment system and the family background of offender.

<sup>&</sup>lt;sup>1</sup> Dr. Abdegalal Osman Idris Abaker. Prof. Assistant of Statistics at Community College in Khamis Mushayt, University of King Khalid, KSA.

<sup>2</sup> Dr Mohammed Ahmed Nour Ali. Prof. Assistant of Sociology and Social Anthropology at Peace Studies & Research Center, University of Nyala, Sudan.

## 1. Introduction

This research studies the situation of crime in South Darfur State (SDS) using factor analysis model

Darfur region of western Sudan is an instable area due to the ongoing war between the government of Sudan and rebel movements since 2002, where weapons are widely spread so local authority is not able to control them. SDS is one of the states forming the geography of the troubled region, located in the southern side of the region which is rich with farmlands and covered by forests and valleys.

Because of the war there are crimes of different types in the state, such as killing, illegal possession of weapons, cultivating and trading drugs Bongo (Local kind of drug), which is attributed to the instability in the region in addition to other reasons such as poverty, ignorance, social and cultural reasons. The nature of the State of forests and farmlands has negatively contributed to make things worse in terms of drug farming, trading and distributing it in other places, especially the capital city of Khartoum. There are some areas in the State which are famous for cultivating Bongo such as the suburbs of Daein, Radoom, Temsaha and Bahrel-Arab areas. Drugs are grown inside the forest in the autumn season, where it is difficult for authorities to access these areas because of the rainfall season and poor watch mechanism, so most of the criminals and other law breakers are able to escape being arrested and punished.

Nyala prison for instance has prisoners of all types of crimes such as murderers, drug dealers and illegal weapon carriers.

The problem of the study: there are a number of reasons (observed variables) of crime in SDS; but are there any unobserved variables (factors) there in. Sometimes it is expected that some unobservable factors exist in such cases as the crime in the State, so what are that unobserved factors in the crime in the State. What are the features of these factors? To what extent the variables that associated with crime could be reduced. The hypotheses to be tested are: the unobserved reason (factors) of crime is not due to the poverty, ignorance, social and cultural factors.

Methodology of the study: The population of the study is the people who commit crimes in the State. The frame of sampling is that the persons whom are captured and punished. The sample size is 667; which is more than twenty times as the variables to be analyzed; it is more acceptable<sup>2</sup>. The Quota sampling was used to collect the data of selected variable in the year 2012 and the respondents selected as volunteers for the sensitivity of the studied case. An analytic procedure will be used to study and analyze the data collected from prisoners in Nyala prison by using factor analysis model. SPSS will be used to analyze the data.

Aims of the study: This research aims to study the underlying structure of the crime in South Darfur State by using factor analysis, and to know to what extent that the data of the crime could be reduced.

**Previous studies:** There are some previous studies used factor analysis in the State; but none of them has been implemented in the field of crime.

## 2 - Factor analysis

Factor analysis is a class of multivariate statistical methods whose primary purpose is to define the underlying structure in data matrix. It addresses the problem of analyzing the structure of the interrelationships (correlations) among a large number of variables by defining a set of common underlying dimensions, known as factors<sup>3</sup>. A major assumption of factor analysis is that it is not possible to observe these factors directly; the variables depend on the factors but they are also subject to random errors<sup>4</sup>.

## 2.1 Factor Analysis Model

The factor analysis model expresses the variation and co-variation in a set of observed continuous variables  $y_{j(j=1...p)}$  as a function of factors  $f_{k(k=1...m)}$  and residuals  $\varepsilon_{j(j=1...p)}$ . For person i:-

$$y_{i1} = v_1 + \lambda_{11}f_{i1} + \lambda_{12}f_{i2} + \dots + \lambda_{1k}f_{ik} + \dots + \lambda_{1m}f_{im} + \varepsilon_{i1}$$

<sup>&</sup>lt;sup>2</sup> Joseph F. Hair, Jr. et al Multivariate Data Analysis, Fifth edition, 1998, Prentice Hall, Inc. New Jersey P(98-99)
<sup>3</sup> Joseph HairP(98 - 99)

<sup>&</sup>lt;sup>4</sup> K. V. Mardiaetel. 1979, Multivariate analysis, Academic press Inc. London. P(255)

$$y_{ij} = \nu_j + \lambda_{j1} f_{i1} + \lambda_{j2} f_{i2} + \dots + \lambda_{jk} f_{ik} + \dots + \lambda_{jm} f_{im} + \varepsilon_{ij}$$

$$y_{ip} = v_p + \lambda_{p1} f_{i1} + \lambda_{p2} f_{i2} + \dots + \lambda_{pk} f_{ik} + \dots + \lambda_{pm} f_{im} + \varepsilon_{ip}$$
 (2.1)

Where:  $v_j$  are intercepts,  $\lambda_{jk}$  are factor loadings,  $f_{ik}$  are factor values and  $\varepsilon_{ij}$  are residuals with zero means and correlations of zero with the factors<sup>5</sup>.

In matrix form the basic factor analysis equation is:-

$$Y = \nu + \Lambda F + \varepsilon$$

Where:- Y is a p×1 vector of variables,  $\Lambda$  is a p×m matrix of factor loadings, F is an m×1 vector of unobservable factors and  $\varepsilon$  is a p×1 vector of unique factors<sup>6</sup>.

# 2.2 Assumptions of the factor model

The underlying statistical assumptions impact factor analysis departure from normality, homoscedasticity, and linearity can diminish correlations between variables<sup>7</sup>. There are technical assumptions such as:

1. 
$$E(F) = 0$$

2. Cov (F) = 
$$E(FF') = I_{m \times m} f \sim N(o, I)$$

3. 
$$E(\varepsilon) = \underline{0}$$

4. 
$$Cov(\varepsilon) = E(\varepsilon \varepsilon') = \Psi_{p \times p} = \begin{bmatrix} \psi_1 & 0 & . & . & 0 \\ 0 & \psi_2 & & . \\ . & 0 & & \\ . & & & \\ 0 & . & & \psi_p \end{bmatrix} \varepsilon \sim N(0, D_{\psi})_{\underline{\hspace{1cm}}} (2.2)$$

5. 
$$Cov(\varepsilon, F) = E(\varepsilon, F') = 0_{p \times m}$$
 That (F and  $\varepsilon$  are independent)

These assumptions let the model, orthogonal factor model<sup>8</sup>.

<sup>5</sup>www.ats.ucla.edu/stat/seminars/muthen 08/part2.pdf

<sup>&</sup>lt;sup>6</sup>Subhash Sharma 1996, Applied Multivariate Techniques, John Wiley & Sons, Inc. New York P(135)

<sup>&</sup>lt;sup>7</sup> Joseph F. Hair, JR. etal 1998 Op. cit. P(121)

<sup>&</sup>lt;sup>8</sup>S. James Press, 1972. Applied Multivariate analysis. Holt, Rinehart and Winston, Inc. New York. P(305)

### 2.3 Correlation matrix (R)

A correlation matrix R is a symmetric matrix with units diagonal and off diagonal elements  $r_{ii'}$  that satisfy:

$$-1 \le r_{ii'} = r_{i'i} \le 1$$
 ,  $j \ne j'$ 

(This relation is necessary but not sufficient)9.

### 2.4 Standardization

Standardization has some important practical implications. Most factor analysis conducted under the condition that the factors are standardized<sup>10</sup>.

#### 2.5 Factor extraction

There are several factor extraction methods at the various statistical software packages to choose from <sup>11</sup>. All calculate a set of orthogonal components or factors that, in combination, reproduce R. Criteria that are used to generate the factors (e. g., maximize variance, minimize residual correlation) differ from technique to another. But the differences between solutions they produce may be small with good data set and a similar communality estimates. A stable solution usually tends to appear regardless of which extraction technique was employed. None of the extraction techniques routinely provides an interpretable solution without rotation <sup>12</sup>.

Principal component PC is one of the most commonly used in extraction factors. The PCs are used to discover and interpret the dependences that exist among the variables, and to examine relationships that may exist among individuals<sup>13</sup>.

<sup>&</sup>lt;sup>9</sup>Robert MacCallum, 2004. Factor analysis class notes, Ohio State University. P(24, 25)

<sup>10</sup> Ledyard R. Tucker, Robert C. MacCallum, 1997. Exploratory factor analysis, University of Illinois, USA. P(67)

<sup>&</sup>lt;sup>11</sup> Anna B. Costello and Jason W. Osborne, 2005. Best Practices in Exploratory Factor analysis: four recommendations for getting the most from your analysis, practical assessment, Research & Evaluation. Vol. 10, No. 7. P(2)

<sup>&</sup>lt;sup>12</sup>Barbara G. Tabachick, Linda. F. Fidell, 1983. Using Multivariate statistics. Harper and Row, Publishers, New York. P(394)

<sup>&</sup>lt;sup>13</sup>Niel H. Timm, 2002. Applied multivariate analysis. Springer Verlag, Newyork Inc.. P(445.)

## 2.6 Factor rotation

Rotations of the factor solution are the common type of constraints placed on the factor model for obtaining a unique solution. There are two types of rotation technique: orthogonal and oblique. Orthogonal rotations result in orthogonal factor models, whereas oblique rotations result in oblique factor models<sup>14</sup>

In an orthogonal factor model it is assumed that  $\Phi = 1$ . Orthogonal rotation technique involves the identification of a transformation matrix C such that the new loading matrix is given by  $\Lambda^* = \Lambda C$  and  $R = \Lambda^* \Lambda^{*'}$ .

The transformation matrix is estimated such that the new loadings results in an interpretable factor structure. Varimax and quartimax are the most commonly used orthogonal rotation techniques for obtaining the transformation matrix<sup>15</sup>

The objective of varimax rotation is to determine the transformation matrix, C, such that any given factor will have some variables that will load very high on it and some that will load very low on it<sup>16</sup>.

## 2.7 Communalities

Communality is the total amount of variance; an original variable shares with all other variables included in the analysis<sup>17</sup>. It is given by:

$$h_j^2 = \lambda_{j1}^2 + \lambda_{j2}^2 + \dots + \lambda_{jp}^2$$
 (2.3)

The size of the communality is a useful index for assessing how much variance in a particular variable is accounted for by the factor solution. High communality values indicate to a large amount of the variance in a variable which has been extracted by the factor solution. Small communalities show that a substantial portion of the variable's variance is not accounted for by the factor<sup>18</sup>.

<sup>&</sup>lt;sup>1414</sup>Subhash Sharma Op. Cit. p 137

<sup>15</sup> Ibid

<sup>&</sup>lt;sup>16</sup> Ibid P(138)

<sup>&</sup>lt;sup>17</sup>Joseph F. Hair, et al, 2010. Multivariate data analysis A Global perspective, seven edition. Pearson Prentice Hall New Jersey. P(92)

There are other ways to estimate the communalities, such as:

$$h_j^2 = r_{jk}r_{jl}/r_{kl} (2.4)$$

$$h_j^2 = \sum_{k=1}^n r_{jk}/n - 1 \tag{2.5}$$

Where k,i are two variables which correlate highest with the given variable. 19.

## 2.8 Kaiser-Meyer-Olkin measure (KMO)

Kaiser-Meyer-Olkin measure is a measure of sampling adequacy. KMO statistics varies from zero to one. A value of 0 indicates that the factor analysis is likely to be inappropriate. A value close to 1 indicates that factor analysis should be appropriate and reliable factors. Kaiser (1974) recommends accepting values greater that 0.5 as acceptable. Furthermore, values between 0.6 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb<sup>20</sup>.

### 2.9 Bartlett's test of sphericity

Barteltt's measure tests the null hypothesis that the original correlation matrix is an identity matrix. For factor analysis we need some relationships between variables and if it were identity matrix then all correlation coefficients would be zero. Therefore we want this test to be significant, which tells us that the R-matrix is not an identity matrix<sup>21</sup>.

<sup>&</sup>lt;sup>19</sup>Harry H. HarmanHarman, 1976. Modern factor analysis 3rd edition. The University of Chicago Press. P(84-87)

Andy Field. 2005. Factor analysis using SPSS. http://www.sagepub.co.uk/field/multiplechoice.html.P(5,6)

# 2. 10Factor loadings

Factor loadings are the correlations of each variable and the factor. Loadings indicate the degree of correspondence between the variable and the factor, with high loadings making the variable representative of the factor. <sup>22</sup> Factor loadings greater than  $\pm 0.30$  are considered to meet the minimal level; loadings of  $\pm 0.40$  are considered more important; and if the loadings are  $\pm 0.5$  or greater, they are considered practically significant<sup>23</sup>.

# 3 - Analyzing the Data of study

# **Definition of variables**

For the purpose of the statistical analysis the variables of the study are defined as below:

Code	Variable	Code	variable				
X <sub>1</sub>	Sex of respondent	X <sub>10</sub>	Number of family members				
X <sub>2</sub>	Age of respondent	X <sub>11</sub>	Number of students in the family				
X <sub>3</sub>	Type of court	X <sub>12</sub>	Psychological situation				
X <sub>4</sub>	Period of jail sentencing	X <sub>13</sub>	Job of respondent				
X <sub>5</sub>	Type of punishment	X <sub>14</sub>	Income of respondent				
X <sub>6</sub>	Item of punishment	X <sub>15</sub>	House building Material				
X <sub>7</sub>	Remaining period of sentence	X <sub>16</sub>	Type of accommodation				
X <sub>8</sub>	Level of education	X <sub>17</sub>	Motives to commit a crime				
X <sub>9</sub>	Marital status						

SPSS were used to analyze the data related to the prisoners collected from prison of Nyala. The correlation matrix was analyzed. To get acceptable factors; SPSS asked to suppress loadings less than 0.3 table (3-5)<sup>24</sup>

24 Ibid

<sup>&</sup>lt;sup>22</sup> Joseph F. Hair, JR. et al 1998Op. Cit P(106)

<sup>&</sup>lt;sup>23</sup> Ibid P(111)

Table (3-1	) Correlation Matrixa
------------	-----------------------

	×4 /-			_	_		_				_		_				_
	Χı	X2	хз	X4	X5	X6	<b>X7</b>	X8	Х9	X10	X11	X12	X13	X14	X15	X16	X17
X1		.104	ķ		.000	.096	ģ	¥	.223		.III.	.041	.156	.166	.007	.010	-123-
X2			.043	.012	.174	-854	.041	15	-1%	.331	.264	.070	-171-	.093	·M·	.152	-111-
Х3				.144	.123	.007	.062	-155	-10	-101-	-115	13)	.156	-203	.067	.036	.047
X4					.016	-451-	.640	.008	-103-	.101	.082	.020	-819-	-171-	.092	.036	149-
X5						.307	-10	.807	.024	.03	.004	#16-	.M-	.020	-163-	.093	.066
Х6				l	İ		-554	-#4	.077	-172-	-872-	.40	.038	.015	.#	.011	.260
X7			1					.054	-##-	.162	.096	.037	-83	-143	.054	.042	-XK-
X8		l							-84	.009	.151	-83-	.201	-m	-2%	.85	.948
X9										-120-	-86-	.090	.032	.038	.03	-413-	.045
X10								ĺ			.595	-817-	-164	.059	.042	.047	-129-
XII												-818-	-313-	.19	-573-	.#5	.K2
		i				{	ļ	ļ					-84	-15	411.	.053	.054
X12					l				ļ		i	١		-457-	507.000	.020	.039
X13									1	1		ļ		1	.169	-011-	86
X14	ŀ						1				١		]		""	.052	.grz.
X15									1	1				1		""	.037-
X16	1					ł	1	l		1		1	l				-WJ/-
X17	L_		<u> </u>		<u> </u>		Ц,		<u> </u>	<u> </u>		<u> </u>	<u> Ц</u>	ــــــــــــــــــــــــــــــــــــــ	ᆫ	Щ.	Ц.

a. Determinant - .961

The correlation matrix table (3-1) shows that there are some relations between the variables and the determinant of the matrix is 0.06 which is not singular so the factor analysis could be applied for this matrix.

Table (3-2) KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure	.620	
•	Approx. Chi-Square	1158.561
Bartlett's Test of Sphericity	df	136
	Sig.	.000

Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) statistics equal to 0.62 which refers that the sample size is mediocre or the sample size is sufficient. Bartlett's Test is highly significant; P-value = 0.000 indicates that the correlation matrix is not Identity matrix; therefore, factor analysis is appropriate. See table (3-2)

Table (3-3) Communalities

variable	Initial	Extraction	variable	Initial	Extraction
X <sub>1</sub>	1.000	.655	X <sub>10</sub>	1.000	.751
X <sub>2</sub>	1.000	.566	X <sub>11</sub>	1.000	.714
X <sub>3</sub>	1.000	.545	X <sub>12</sub>	1.000	.744
X <sub>4</sub>	1.000	.710	X <sub>13</sub>	1.000	.721
X <sub>5</sub>	1.000	.726	X <sub>14</sub>	1.000	.682
X <sub>6</sub>	1.000	.692	X <sub>15</sub>	1.000	.623
X <sub>7</sub>	1.000	.776	X <sub>16</sub>	1.000	.304
X <sub>8</sub>	1.000	.623	X <sub>17</sub>	1.000	.571
X <sub>9</sub>	1.000	.515			

Extraction Method: Principal Component Analysis.

Table (3-3) is the table of communalities. The second column is the variances of all variables; for standardization they are equal to one. The third column shows the variances after extraction. Only one variable (Type of accommodation) has communality less than 0.5 so this variable could be ignored when interpreting the solution<sup>25</sup>.

Table (3-4) Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.490	14.647	14.647	2.490	14.647	14.647	2.237	13.157	13.157
2	1.966	11.566	26.213	1.966	11.566	26.213	1.845	10.854	24.010
3	1.709	10.052	36.265	1.709	10.052	36.265	1.634	9.610	33.620
4	1.381	8.121	44.386	1.381	8.121	44.386	1.408	8.281	41.902
5	1.192	7.010	51.395	1.192	7.010	51.395	1.360	8.002	49.904
6	1.162	6.837	58.232	1.162	6.837	58.232	1.344	7.905	57.809
7	1.019	5.997	64.229	1.019	5.997	64.229	1.091	6.420	64.229
8	.978	5.752	69.981						
9	.890	5.238	75.219						
10	.759	4.464	79.683						ì
11	.667	3.924	83.607						
12	.619	3.642	87.249						
13	.572	3.367	90.616						
14	.485	2.850	93.466						
15	.430	2.529	95.996						
16	.367	2.160	98.155						
17	.314	1.845	100.000						

Extraction Method: Principal Component Analysis.

<sup>&</sup>lt;sup>25</sup> Joseph F. Hair, JR. et al 1998 Op. cit. P(113)

Table (3-4) shows the total variance explained. In this table the initial eigenvalues and extraction and rotation sums of squared loadings are displayed. According to Kaiser Criterion only seven factors are extracted.

Table (3-5) Rotated Component Matrixa

Table	e (3-5) Rotated Component Matrixa							
	Component							
	1	2	3	4	5	6	7	
X7	.871							
X4	.820				1			
X6	751-				1	.308		
X10		.853						
X11		.824			i			
X2		.574				.442		
X13			.826			1		
X14			786-	1000000 1100				
X3			.446	.302	322-	.379		
X15				.771				
X8				718-				
<b>X</b> 1					.755			
X9					.628			
X5		ŀ		ŀ	·	.814		
X16		l	1	l	<u> </u>	.433		
X12		1		1			.841	
X17	388-				384-		.491	

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

The factor structure for the crime in the State is displayed in table (3-5); this table contains the loading of each manifest variable on the factor associated with.

### 4 - Discussion

# 4.1 Interpretation of the factors

The interpretation of the factor analysis model is greatly simplified if most of the loadings corresponding to manifest variable are zero. This means that the manifest variable is influenced by a small number of factors only. We use the factor loadings to understand what the factors are and to name them. What is the first factor? We look at the first column of factor loadings in the factor matrix. High loadings show which variables are strongly influenced by the first factor. Near zero loadings

show which variables are not influenced appreciably by the first factor. A characteristic that is shared by the variables that have high loadings will suggest what effect the factor has and enable the investigator to name this factor<sup>26</sup>.

The data of crime in SDS could be reduced from seventeen variables to only seven factors to explain 64.29 % of variance. These factors were extracted according to the Kaiser criterion (eigenvalues of one or more). As shown in table (3-4). These factors will be discussed to know their nature and naming them in order to interpret each factor.

## The first Factor:

The first factor explains 13.157 % of the total variance of the crime in the State. Three manifest variables loaded significantly on it, the highest one is the remaining time of punishment which loaded by (0.871) then the total time of punishment amount (0.82) and the item of punishment (-0.751) table (4-1). These entire variables are related to the punishment system so the best name for this factor is the (punishment system).

Table (4-1) Structure of the first Factor

No.	Variable	Loading
1	remaining Period of sentencing	0.871
2	Period of jail sentencing	0.82
3	item of punishment	0.751

The source: Prepared by the researcher depending on SPSS output

## The second factor

The results of rotated axes of factor analysis as in table (3-4) show that the second factor explained 10.85% of total variance of the crime. There are three observed variables loaded significantly on it table (4-2); the number of family members loaded by 0.853, the Number of students in the family loaded by 0.824 and the age of the respondent loaded by 0.574. All these variables are related to the family of the offender; so the suggested name for this factor is the (family of the offender).

Table (4-2) Structure of the second Factor

No.	Variable	Loading
1	Number of family members	.853
2	Number of students in the family	.824
3	Age of respondent	.574

The source: Prepared by the researcher depending on SPSS output

<sup>&</sup>lt;sup>26</sup>Robert MacCallumcit P(119)

### The third factor

The third factor was loaded by three variables table, (3-5) and explained more than 9.6% of the total variance, table (3-4). These variables include the job of the respondent, the income and the Type of court; the loading of these variables are 0.826, -0.786 and 0.446 respectively, table (4-3). The two variables of high loadings are belonging to the level of life; the researcher names this factor the life style of the offender.

Table (4-3) Structure of the third Factor

No.	Variable	Loading
1	Job of respondent	.826
2	Income of respondent	786-
3	Type of court	.446

The source: Prepared by the researcher depending on SPSS output

### The fourth factor

As shown in table (4-4) there are three variables loaded significantly on this factor; type of court account 0.302, the house building material 0.771 and the level of education -0.718. As shown in table (3-4) a percentage of 8.28 % of total variance was explained by this factor. The two high loaded variables on this factor are related to social situation of the respondent so the name of this factor is (Social situation).

Table (4-4) Structure of the fourth Factor

1 0010	(+ +) bu detaile of the fourth I deter	
No.	Variable	Loading
1	Type of court	.302
2	House building material	.771
3	Level of education	718-

The source: Prepared by the researcher depending on SPSS output

#### The fifth factor

As shown in the results of orthogonal rotation of the factors table (3-4) a proportion of 8% of the total variance was explained by this factor. The variables that significantly loaded on the fifth factor are the type of court -0.322, sex 0.755, marital status 0.628 and motives for commit a crime-0.384 table (4-5). These variables are of different types; but the high loaded one is the sex so it can be named the (Sex of offender).

Table (4-5) Structure of the fifth Factor

(	1 5) Buildetaile of the firm I motor	
No.	Variable	Loading
1	Type of court	322-
2	Sex of respondent	.755
3	Marital status	.628
4	Motives to commit a crime	384-

The source: Prepared by the researcher depending on SPSS output

# The sixth factor

The last interpreted factor of this factor model as seen in table (3-5) explained about 8% of the total variance table (3-4). Five variables are loaded on this factor; the highest one is the type of punishment loaded by 0.814; see table (4-6); the rest of variables are the item of punishment loaded by 0.308, age by 0.442, type of court by 0.379. The last one is the type of accommodation which would be ignored for its communality of less than 0.5<sup>27</sup>. Most of these variables are related to the judgment system; the suitable name for this factor is (Judgment system).

Table (4-6) Structure of the sixth Factor

No.	Variable	Loading
1	Item of punishment	.308
2	Age	.442
3	Type of court	.379
4	Type of punishment	.814
5	Type of accommodation	.433

The source: Prepared by the researcher depending on SPSS output

# The seventh factor

Although this factor explained more than 6.4% of the total variance but it is undefined that only two variables loaded on it<sup>28</sup>.

## 4.2 Conclusions

The collected data of crime in SDS were analyzed using factor analysis model. For extraction the principal component was chosen and varimax for rotation; for number of factors the Kaiser criterion (eignvalues one or more) was used. After the results of analysis discussed; some results were reached as below:

<sup>&</sup>lt;sup>27</sup> Joseph F. Hair, JR. et al 1998 Op. cit. P(113)

<sup>&</sup>lt;sup>28</sup>Mustafa HusienBahi, etal, 2002. Factor analysis, the theory and application, Book Center Press, Cairo. P(44) (In Arabic)

- -The results of the orthogonal rotation of factor analysis show that the data of seventeen observed variables of crime in the State could be reduced to only seven factors to explain about 64.23% of the total variance in crime situation in the State.
- -Six factors out of the seven are interpreted; they are punishment system, family background of the offender, life style of the offender, Social situation, sex and Judgment system. The seventh factor is unidentified as a few number of variables that are loaded on it.
- -The most important factors are the punishment system and family background; they are explained more than 24% of the total variance in the crime. The punishment system explained about 13.2% and the family background explained about 10.85% of the total variance.
- -Three observed variables loaded significantly on each of the first five factors. The remaining Period of sentencing, total Period of sentencing and item of punishment are loaded on the first factor. The Number of family members, Number of students in the family and Age of respondent are loaded on the second factor.

### 4.3 Recommendations

According to the results the researcher recommended the following:-

- Competent authorities in the State should deal with crime through six factors instead of all variables related; these six factors are punishment system, family background, life style of the offender, Social situation, sex of the offender and Judgment system.
- Competent authorities should concentrate more on the punishment system and the family background of the offenders.
- Statisticians and crime researcher together with law researchers should cooperate to make relevant researches using factor analysis for more reliable results to handle high crime rate in the State.

#### References

1. Costello, Osborne, 2005. Best Practices in Exploratory Factor analysis: four recommendations for getting the most from your analysis, practical assessment, Research & Evaluation. Vol. 10, No. 7.

- 2. Tabachick, Barbara G, Fidell, Linda F 1983. Using Multivariate statistics. Harper and Row, Publishers, New York.
- 3. Harman, Harry H. 1976. Modern factor analysis 3rd edition. The University of Chicago Press.
- 4. Hair, et al, 2010. Multivariate data analysis A Global perspective, seventh edition. Pearson Prentice Hall New Jersey.
- 5. Hair, et al 1998 Multivariate Data Analysis, Fifth edition, Prentice Hall, Inc. New Jersey.
- 6. Mardiaetel, K. V. 1979, Multivariate analysis, Academic press Inc. London.
- 7. Tucker, Ledyard R. MacCallum, Robert C. 1997. Exploratory factor analysis, University of Illinois, USA.
- 8. Bahi, Mustafa Hussein etal, 2002. Factor analysis, the theory and application, Book Center Press, Cairo. (In Arabic)
- 9. Timm, Niel H. 2002. Applied Multivariate analysis. Springer Verlag, Newyork Inc.
- 10.MacCallum, Robert 2004. Factor analysis class notes, Ohio State University.
- 11.S. James Press, 1972. Applied Multivariate analysis. Holt, Rinehart and Winston, Inc. New York.
- 12. Sharma, Subhash 1996, Applied Multivariate Techniques, John Wiley & Sons, Inc. New York.
- 13.www.ats.ucla.edu/stat/seminars/muthen\_08/part2.pdf
- 14. <a href="https://www.sagepub.co.uk/field/multiplechoice.html">www.sagepub.co.uk/field/multiplechoice.html</a>. Andy Field. 2005. Factor analysis using SPSS.