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Using Factor Analysis method to Identify Factors Affecting Eye Patients

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Abstract: This research deals with the most important factors affecting eye diseases using the factor analysis method. Tests for this method were conducted: The measure of sampling adequacy test (KMO) was = 0.716 and is considered good. In addition, the Chi-Square test was significant (0.00), which is less than 0.05, the random sample of the research was taken (255) eye patients in one of the eye hospitals in Iraq.

The research included focusing on (8) independent variables that affect patients according to the opinion of ophthalmologists, These variables were reduced to (4) factors using the principal component method, and these factors contributed to explaining a variance amounting to (60.512%) of the total variance percentage, after that, these factors were rotated using the Promax method to determine the percentage of contribution of the research variables in forming each of the factors that the researcher arrived at.

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استخدام أسلوب التحليل العاملي لتحديد العوامل المؤثرة على مرضى العيون

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المستخلص

يتناول هذا البحث أهم العوامل تأثيراً على إمراض العيون باستخدام أسلوب التحليل العاملي، وتم إجراء الاختبارات الخاصة بهذا الأسلوب: اختبار مقياس كفاية العينة (KMO) = 0.716 وتعتبر جيدة، فضلاً عن ذلك كان اختبار(Chi-Square) ذات دلالة إحصائية = 0.00 وهي أقل من 0.05، وقد شملت عينة البحث العشوائية (255) شخص من مرضى العيون في احد مستشفيات العيون في العراق، وتضمن البحث التركيز على (8) متغيرات مستقلة تؤثر على المرضى حسب رأي أطباء العيون، اختزلت هذه المتغيرات إلى (4) عوامل باستخدام طريقة المكونات الرئيسية (Principal Component)، وساهمت هذه العوامل في تفسير تباين بلغ (60.512%) من نسبة التباين الكلية، بعد ذلك تم تدوير هذه العوامل بطريقة (Promax) لمعرفة نسبة مساهمة متغيرات البحث في تكوين كل عامل من العوامل التي توصل إليها الباحث.

الكلمات المفتاحية: التحليل العاملي، اختبار كفاية العينة، مرضى العيون، المكونات الرئيسي، تدوير العوامل.

Introduction

When conducting any study or research, it is necessary to take a number of independent variables to know their effect on the subject of the study, and sometimes the researcher finds it difficult to obtain accurate results due to the correlation coefficients between these variables. From here came the idea of factor analysis: which aims to extract a group of the factors related to the variables. These factors explain the largest possible percentage of the variance in the study variables.

The task of factor analysis is to reduce the variables of the study to the smallest possible number of factors, so that each factor has a function linking a group of variables, and the relationship between the variables and factors can be represented in the following formula:

$$F_q = a_{q1}x_1 + a_{q2}x_2 + \cdots + a_{qp}x_p \quad \text{... (1)}$$

Where p: the number of variables and q: the number of factors, and the number of factors is less than the number of variables, Thus, we can say that the task of factor analysis is to reduce data, remove duplicates in a group of interrelated variables, and obtain relatively independent factors.

Research objective: The research aims to use factor analysis to determine which of the factors mentioned in this research affect the eye.

The theoretical side: The factor model interprets (p) of the observed variables for a sample size (n) on the basis of a linear function for (q) from the common factors such that (q<p) and (p) are the only factors for each variable, and the formula (1) explains this (Saeed, 2018: 510):

$\underline{X}_{p.1} = A_{p.q}\,\underline{F}_{q.1} + \underline{U}_{p.1} + \underline{m}$ ...(2)

Since:

$\underline{X}$: Random vector of observed variables.

A: Factor loading matrix.

$\underline{F}$: Random vector common factors.

$\underline{U}$: Random vector unique factors.

$\underline{m}$:Vector means of variables.

If we assume that the vector of the means of the variables is zero, then the vector of means for both the common factors and the unique factors is a zero vector, meaning that (Wedad and Nadia, 2020: 461):

$E(\underline{X}) = \underline{m}=0$

$$E\begin{bmatrix}\underline{F}\\ \underline{U}\end{bmatrix} = \begin{bmatrix}0\\0\end{bmatrix} \quad ...(3)$$

Therefore, the factor model will be as follows:

$\underline{X}_{p.1} = A_{p.q}\,F_{q.1} + \underline{U}_{p.1}$ ...(2)

The covariance matrix for each of U and F (assuming they are independent):

$$E\begin{bmatrix}\underline{F}\\ \underline{U}\end{bmatrix}\begin{bmatrix}\underline{\acute{F}} & \underline{\acute{U}}\end{bmatrix} = \begin{bmatrix}E(\underline{F}\,\underline{\acute{F}}) & E(\underline{F}\,\underline{\acute{U}})\\ E(\underline{U}\,\underline{\acute{F}}) & E(\underline{U}\,\underline{\acute{U}})\end{bmatrix} = \begin{bmatrix}\Phi q.q & 0q.p\\ 0p.q & \Psi p.p\end{bmatrix} \quad ...(4)$$

Since:

Φ: Covariance matrix of common factors.

Ψ:The diagonal covariance matrix of the unique factors (U) has the diagonal elements$(\Psi_1^2, \Psi_2^2, \dots, \Psi_m^2)$ and the off-diagonal elements equal to zero.

The covariance matrix for x is:

$$E[(x-m)(x-\acute{m})] = \sum p.p \quad ...(5)$$

Since:

∑: Symmetric positive definite matrix and of order p.

In factor analysis, the original variables are transformed into new standardized variables distributed normally with an mean of zero and a variance of one $x_i \backsim N(0,1)$ in order to get rid of the different units of measurement for the variables and facilitate the calculations.

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The main model of factor analysis can be formulated if it is assumed that there are (q) factors with the standard value:

$$Z_{ij} = a_{j1} F_1 + a_{j2} F_2 + \cdots + a_{jq} F_q + U_{ji} \quad \dots (6)$$

Since:

Z_{ij}: The standard value of the variable j.

a_{jq}: The saturation value of factor (q) for variable j.

F_q: Standard value of factor (q).

U_{ji}: The standard value of the unique factors.

Estimating the coefficients or loadings $(a_{j1}, a_{j2}, \dots, a_{jq})$ for the factors, the factors are variables with the slight difference that the variables include a direct measurement, while the factors are hypothetical variables that we obtain by analytically processing a group of variables, The factor loadings are correlation coefficients between the variables and the extracted factors (Al-Jadaimi, 2023: 49- 50).

The total variance of the variables is divided into three parts, as shown in the equation: Total variance= Common variance + Specific variance + Error variance.

Part I: Covariance: It is also called the common variance or commonness quantities, and this part of the total variance is associated with the rest of the other variables of common factors and is symbolized by (h^2):

$$h_j^2 = a_{j1}^2 + a_{j2}^2 + \cdots + a_{jq}^2 = \sum_{i=1}^{q} a_{ij}^2 \quad j = 1,2,\dots,p \quad \dots (7)$$

a_{ij}^2: the weight of factor (i) for variable (j) and is the coefficients of the factor matrix.

One of the properties of the common quantity (h_j^2) is that it is positive and its value is limited $(0 \le h_j^2 \le 1)$, it represents the extent of interaction between the variables and extracted factors (Baeshen, 2021: 201)

- If (h_j^2) for the variable is large and close to (1), this means that this variable completely overlaps with the extracted factors.
- If (h_j^2) for one of the variables is equal to zero, then the factor loadings for that variable will be zero, meaning that the extracted factors could not explain any part of the variance of that variable.

- If (h_j^2) falls between zero and one, this indicates partial interference between the variables and factors.

Part II: Specific variance: This part of the total variance is not related to the rest of the variables, but rather to the variable itself, and it is part of the variance of the unique factor:

$$U_j^2 = b_j^2 + e_j^2 \quad ...(8)$$

Since:

U_j^2: Unique factor variance.

b_j^2: The variance of the variable j.

e_j^2: Error variance.

Part III: Error variance: This part of the total variance results from errors in drawing or measuring the sample or any external changes that lead to instability in the data:

$$e_j^2 = 1 - (h_j^2 + b_j^2) \quad ...(9)$$

Both common variance and idiosyncratic variance contribute to forming the reliable variance, which is:

$$r_{jj} = h_j^2 + b_j^2 \quad ...(10)$$

Factor analysis aims to analyze the common variance to determine the number and type of common variances that lead to the correlation of variables, the total variance of the variables Z_j can be represented by the following relationship:

$$\sigma_j^2 = \sigma_{j1}^2 + \sigma_{j2}^2 + \ ... + \sigma_{jq}^2 + \sigma_{js}^2 + \ \sigma_{je}^2 \quad ...(11)$$

Since:

σ_j^2: Total variance.

$\sigma_{j1}^2, \sigma_{j2}^2, ... \sigma_{jq}^2$: Common variance.

σ_{js}^2: Specific variance.

σ_{je}^2: Error variance.

Dividing both sides of the equation by σ_j^2 results in:

$$1 = a_{j1}^2 + a_{j2}^2 + \ ... + a_{jq}^2 + b_j^2 + \ e_j^2 \quad ...(12)$$

The square root values of the covariance of (a_{j1}^2, a_{j2}^2,…,a_{jq}^2) are called factor loadings and represent the amount of correlation for the variable (j) for each factor.

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From the relationships mentioned previously, we can formulate it as follows:

$$1 = h_j^2 + b_j^2 + e_j^2 = h_j^2 + u_j^2 \quad \dots (13)$$

The formula (13) represents the total variance, The reliable variance is represented by the formula (14):

$$r_{jj} = h_j^2 + b_j^2 = 1 - e_j^2 \quad \dots (14)$$

The communism equation can be formulated with the following equation (15):

$$\mathrm{h}_\mathrm{j}^2 = \mathrm{a}_{\mathrm{j}1}^2 + \mathrm{a}_{\mathrm{j}2}^2 + \cdots + \mathrm{a}_{\mathrm{jq}}^2 = 1 - \mathrm{u}_\mathrm{j}^2 \quad \dots (15)$$

The Unique variance is formulated with the following equation(16):

$$\mathrm{u}_\mathrm{j}^2 = \mathrm{b}_\mathrm{j}^2 + \mathrm{e}_\mathrm{j}^2 = 1 - \mathrm{h}_\mathrm{j}^2 \quad \dots (16)$$

The special variance can be represented by the following formula (17):

$$\mathrm{b}_\mathrm{j}^2 = \mathrm{u}_\mathrm{j}^2 - \mathrm{e}_\mathrm{j}^2 \quad \dots (17)$$

Finally, the error variance can be formulated with the equation(18):

$$\mathrm{e}_\mathrm{j}^2 = 1 - \mathrm{r}_{\mathrm{jj}} \quad \dots (18)$$

There are several methods for factor analysis, and the most accurate and common of these methods is the principal components method, which works to reduce a number of related variables to unrelated variables (orthogonal) with the least possible loss of information when the reduction is carried out.

Each component is a linear interaction of the research variables, and their variance gives an indicator that explains part of the total variance, as the variance of the first principal component (λ_1) is greater than the variance of any other principal component, and the variance of the second principal component (λ_2) is less than the variance of the first principal component (λ_1). But it is greater than the variance of any other principal component...etc. ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0$) (Farag, 2023, 213).

The value Eigenvalue is a measure of the size of the variances in all the variables that are calculated on one factor, and it will be used for comparison and not as a percentage to explain the variance. If the value is greater than one, the factor is accepted, but if its value is less, the factor is rejected.

The factor analysis matrix contains correlations. Extracted factors will be obtained, which are axes that are perpendicular to each other and indicate the saturation state of the variables and their coordinates. They are determined in random ways, and the determination process varies from one way to another. This is the concept of factor rotation, and in this research the promax method was chosen.

Before choosing the factor analysis method, it is necessary to conduct the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO), The observed correlation coefficient values are compared with the partial correlation coefficient values, as shown in formula (19):

$$\mathbf{KMO} = \frac{\sum\sum_{i\neq j} r_{ij}^2}{\sum\sum_{i\neq j} r_{ij}^2 + \sum\sum_{i\neq j} p_{ij}^2} \quad \text{... (19)}$$

Since:

r_{ij}: It represents the simple correlation coefficient between variables.

p_{ij}: It represents the partial correlation coefficient between variables.

Its value is limited to $(0 \leq \text{KMO} \leq 1)$, If the value of (KMO) is small, this is an indication that it is not possible to use factor analysis. In general, if the value of $(\text{KMO} < 0.5)$ is small, then this method is not possible (Al-Fardawi, 2019, 313)

The practical side: The eye is the most sensitive organ from the rest of the body, both functionally and anatomically, Environmental factors, lifestyles, behaviour, and daily practices of the individual may cause damage to the eye. Caution must be taken because the eye is the organ that can diagnose diseases before they are felt by the veins and arteries.

In this research, (255) random samples of eye patients in one of the eye hospitals in Iraq were selected, and the most important explanatory variables agreed upon by most ophthalmologists were taken, which are (8) variables, as shown in Table No (1).

Table No (1) shows a description of the independent variables according to categories, and their frequencies and percentages were calculated, as well as the arithmetic mean and standard deviation for each of the research variables:

Table (1): Descriptive statistics for independent variables

Explanatory variables		Frequency	Percentage	Mean	Std. Dev.
x_1: Age	(1) children	52	20.4%	2.200	.7553
	(2) youth	100	39.2%		
	(3) elderly	103	40.4%		

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<table>
<tr><th colspan="2">Explanatory variables</th><th>Frequency</th><th>Percentage</th><th>Mean</th><th>Std. Dev.</th></tr>
<tr><td rowspan="2">x2: Gender</td><td>(1) Male</td><td>142</td><td>55.7%</td><td rowspan="2">1.443</td><td rowspan="2">.4977</td></tr>
<tr><td>(2) Female</td><td>113</td><td>44.3%</td></tr>
<tr><td rowspan="3">x3: Monthly income</td><td>(1) Enough</td><td>111</td><td>43.5%</td><td rowspan="3">1.770</td><td rowspan="3">.7793</td></tr>
<tr><td>(2) Somewhat enough</td><td>91</td><td>35.7%</td></tr>
<tr><td>(3)Enough not</td><td>53</td><td>20.8%</td></tr>
<tr><td rowspan="3">x4: Optic nerve</td><td>(1) Natural</td><td>108</td><td>42.4%</td><td rowspan="3">1.671</td><td rowspan="3">.6409</td></tr>
<tr><td>(2) Middle</td><td>123</td><td>48.2%</td></tr>
<tr><td>(3) Little</td><td>24</td><td>9.4%</td></tr>
<tr><td rowspan="3">x5: Vision level</td><td>(1) Natural</td><td>86</td><td>33.7%</td><td rowspan="3">2.055</td><td rowspan="3">.8540</td></tr>
<tr><td>(2) Middle</td><td>69</td><td>27.1%</td></tr>
<tr><td>(3) Little</td><td>100</td><td>39.2%</td></tr>
<tr><td rowspan="3">x6: Urea ratio</td><td>(1) Natural</td><td>98</td><td>38.4%</td><td rowspan="3">1.773</td><td rowspan="3">.7010</td></tr>
<tr><td>(2) Middle</td><td>117</td><td>45.9%</td></tr>
<tr><td>(3) High</td><td>40</td><td>15.7%</td></tr>
<tr><td rowspan="3">x7: Diabetes level</td><td>(1) Natural</td><td>101</td><td>39.6%</td><td rowspan="3">1.769</td><td rowspan="3">.7136</td></tr>
<tr><td>(2)Middle</td><td>112</td><td>43.9%</td></tr>
<tr><td>(3) High</td><td>42</td><td>16.5%</td></tr>
<tr><td rowspan="3">x8: Eye pressure</td><td>(1) Natural</td><td>83</td><td>32.5%</td><td rowspan="3">1.949</td><td rowspan="3">.7744</td></tr>
<tr><td>(2) Middle</td><td>102</td><td>40.0%</td></tr>
<tr><td>(3) High</td><td>70</td><td>27.5%</td></tr>
</table>

The correlations between the research variables are known, it becomes clear to there is a strong correlation in the correlation matrix, another perfect correlation, and sometimes there is no correlation,...etc. After that, it must be known whether the sample is appropriate or not, and the measure of sampling adequacy test (KMO) shows this as in Table No.(2):

Table (2): KMO and Bartlett's Test

<table>
<tr><th colspan="2">Kaiser-Meyer-Olkin Measure of Sampling Adequacy</th><td>.716</td></tr>
<tr><th rowspan="3">Bartlett's Test of Sphericity</th><th>Approx. Chi-Square</th><td>59.426</td></tr>
<tr><th>Df</th><td>28</td></tr>
<tr><th>Sig.</th><td>.000</td></tr>
</table>

From Table No. (2), it is clear that the value of measure of sampling adequacy (KMO) is (.716), and since it is greater than (.70), this indicates that the measurement is good, while the value of the (Chi-Square) test is significant and statistically significant, as it is less than (0.05).

Table (3): Communalities

Variables	Initial	Extraction
x_1: Age	1.000	.593
x_2: Gender	1.000	.709
x_3: Monthly income	1.000	.478
x_4: Optic nerve	1.000	.542
x_5: Vision level	1.000	.708
x_6:Urea ratio	1.000	.613
x_7: Diabetes level	1.000	.545
$x_{8:}$ Eye pressure	1.000	.653

Table No. (3) shows the degrees of commonness among the variables when using the principal components analysis method, it also shows that the highest variable is gender, and the lowest is monthly income.

Table (4): Total variance explained (Eigen values of factors)

Component	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	Variance	Cumulative	Total	Variance	Cumulative	Total
1	1.467	18.341%	18.341%	1.467	18.341%	18.341%	1.407
2	1.223	15.291%	33.632%	1.223	15.291%	33.632%	1.171
3	1.118	13.972%	47.603%	1.118	13.972%	47.603%	1.170
4	1.033	12.909%	60.512%	1.033	12.909%	60.512%	1.080
5	.871	10.888%	71.400%				
6	.857	10.715%	82.116%				
7	.758	9.481%	91.597%				
8	.672	8.403%	100.000%				

Table No. (4) shows the interpretation of variance and reducing the variables to a number of factors, The number of factors has become less than the number of variables, which were eight, and they were reduced to (4) factors, The four factors explain (60.512%) of the total variance.

The first (4) factors are the ones with the greatest Eigenvalue of the ones that come after them, and if it is greater than 1, it is accepted as a factor, but if it is less than 1, it rejects and does not pass as a factor, Therefore, we find that the value of the Eigenvalue of the first factor (1.467) > the value of the Eigen value of the second factor (1.223) > the value of the Eigenvalue of the third factor (1.118) > the value of the Eigenvalue of the fourth factor (1.033), while the rest of the latent roots are less than 1.

The table above shows the Eigenvalue of the correlation matrix (component variance), where it is noted that the first principal component has the largest Eigenvalue (variance) = 1.467 and explains (18.341%) of the total variances, in general, the percentage of variance explained for the component = Eigenvalue / sum of Eigenvalue (number of variables) * 100, For example: Percentage contribution to the total variance of the first principal component = 1.467/8 = 18.341%.

The percentages of explaining variances from the total variance for each factor separately were also reached, as the Eigenvalue is a criterion for each component of the variance it can reveal, the higher the value of the Eigenvalue, the greater the variance that the factor explains or reveals (Ahmed and Ismail, 2021: 466), scree plot the following explains this more.

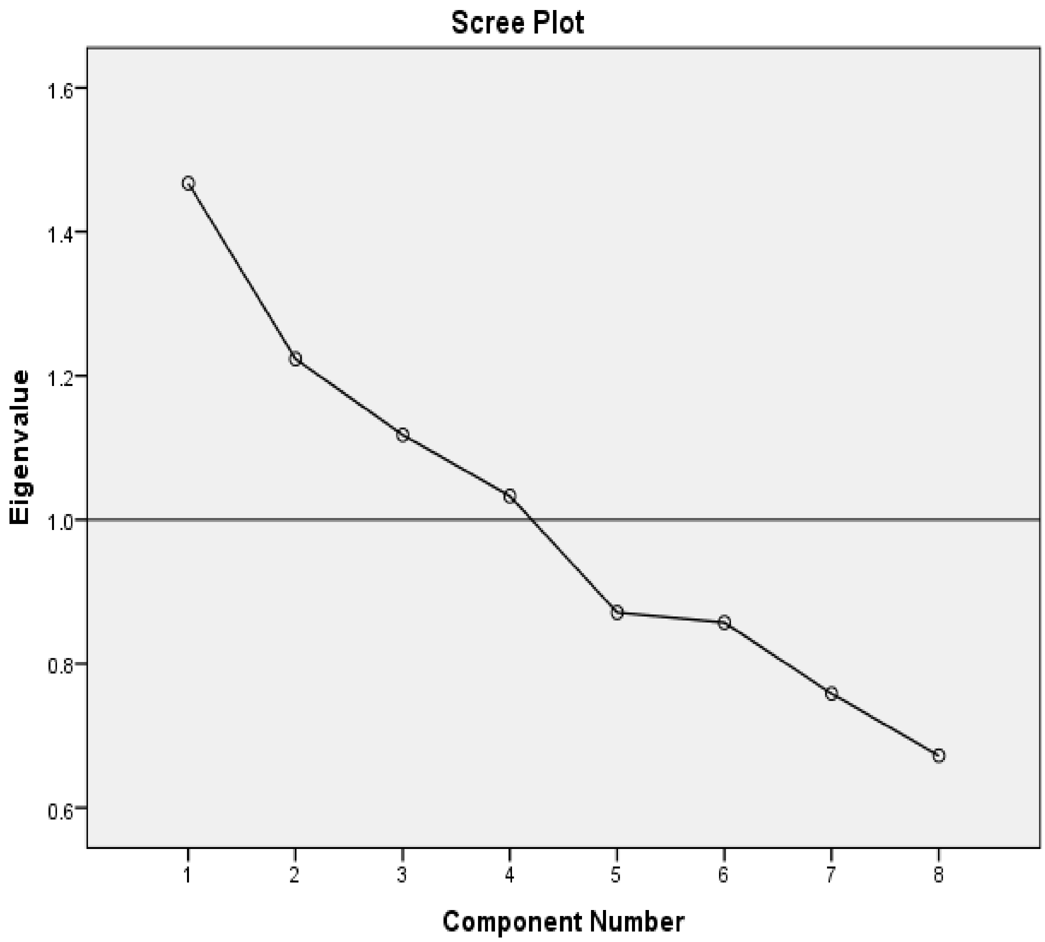

Figure (1): Eigen values of factors

Source: Prepared by the researcher using SPSS.

A figure (1) showing the Eigenvalue values, where the y-axis represents the factors, and the x-axis represents the component numbers (Al-

Qenawi and Naeem, 2021, 66), It is also clear from the figure that there are (4) factors greater than 1, whose location is above the straight line, while factors less than 1 are located below the straight line.

Table (5): Factor matrix after rotation

	Component			
	F_1	F_2	F_3	F_4
x_6:Urea ratio	.775			
x_7: Diabetes level	.714			
x_8: Eye pressure		.742		.372
x_4: Optic nerve		.617		
x_3: Monthly income		-.486	-.345	
x_2: Gender			.847	
x_1: Age	.440		.470	
x_5: Vision level				.848

Table No. (5) shows the percentage of contribution of the eight research variables in forming each of the four factors after performing a rotation of the factors extracted by the promax method, the following are the factors extracted from the variables:

First factor (F_1): This factor explains (18.341%) of the total variance. Three variables contributed to the formation of this factor (**x_6 :Urea** ratio**, x_7:** Diabetes level**, x_1:** Age) and are ranked from highest to lowest.

$$F_1 = 0.775\, x_6 + 0.714\, x_7 + 0.440\, x_1$$

Second factor (F_2): This factor explains (15.291%) of the total variance. Three variables contributed to the formation of this factor (**x_8:** Eye pressure**, x_4:** Optic nerve**, x_3:** Monthly income) and are ranked from highest to lowest.

$$F_2 = 0.742\, x_8 + 0.617\, x_4 - 0.486\, x_3$$

Third factor (F_3): This factor explains (13.972%) of the total variance. Three variables contributed to the formation of this factor (**x_2:** Gender**, x_1:** Age**, x_3:** Monthly income) and are ranked from highest to lowest.

$$F_3 = 0.847\, x_2 + 0.470\, x_1 - 0.345\, x_3$$

Forth factor (F_4): This factor explains (12.909%) of the total variance. Two variables contributed to the formation of this factor (**x_5:** Vision level**, x_8:** Eye pressure) and are ranked from highest to lowest.

$$F_4 = 0.848\, x_5 + 0.372\, x_8$$

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Conclusions

1. The measure of sampling adequacy test (KMO)= 0.716 and is considered good. In addition, the Chi-Square test was significant (0.00).
2. Reduction of research variables (8) to (4) factors using the principal component method.
3. The contribution of these factors (4) in the interpretation of the variance of speech (60.512%) is the percentage of total variance.
4. The topic of rotation of the factors by Promax method to know the percentage of the research variables in the formation of the total factor of the four factors.

Recommendations

1. It is necessary to use factor analysis when data is collected through a questionnaire, as it includes a large number of variables, so it is reduced to fewer factors.
2. It is preferable to use more than one method to determine the degrees of commonality between variables and compare the results between the methods.
3. When performing rotation, it is necessary to choose the appropriate method for the data in the area of research.
4. We verify the results reached by corroborating them using confirmatory factor analysis(CFA).
5. It is necessary to add other information to the patient's record, such as (educational status, type of work, is the disease hereditary ...etc.).

References:

1. Saeed, Azad Abdullah, "Using factor analysis to explain the factors affecting the causes of delayed pregnancy in Sulaymaniyah Governorate", Scientific Journal of Cihan University, Sulaymaniyah, Issue (2), Volume (2), 2018, pp.507-521.
2. Wadi, Wedad and Nadia, "Analyzing sustainable development indicators in Iraq using the factor analysis method", Tikrit Journal of Administrative and Economic Sciences, Tikrit University, College of Administration and Economics, Volume (16), Issue (52) Part (3), 2020, pp. 455- 473.
3. Al-Jadaimi, Youssef Ibrahim, "Exploratory and confirmatory factor analysis of the dimensions of information staff's communication style in special terms and the extent of retention of those who frequent them," Economic Studies Journal, Faculty of Economics, Sirte University, Vol.6, No.1, January, 2023, pp. 41-83.
4. Baeshen, Hoda Muhammad Saleh, "Factor analysis to determine the factors of characteristics that must be present in a university professor" Hadhramout University Journal for the Human Sciences, Volume 18, Issue 1, June, 2021, pp. 195-224.

5. Farag, Eyman Musa Farag, “Using Exploratory factor analysis and Cluster Analysis in classifying the factors affecting the low level of intermediate education students from the teachers' point of view", African Journal of Advanced Pure and Applied Sciences, Volume 2, Issue 2, April-June, 2023, pp. 206-218.
6. Al-Fardawi, Ali Muhammad Ali, “Using the method of Factor Analysis to determine the factors Affecting divorce rate: An applied study in Mayson province“, Journal of Management and Economics, University of Maysan, Issue (118), Volume (42), 2019, pp.309-319.
7. Ahmed, Sally and Ismail, “Using factor analysis to identify the most important factors Influencing indicators of sustainable development of universities Al-Iraqiya”, Iraqi University Journal, Issue 47, Part 1, 2021, pp. 462-476.
8. Al-Qenawi, Khaled and Naeem, “Using Factor Analysis to Specify the Most Important Factors Which Affect the Academic Achievement at Students of Secondary Level", White Nile Journal for Studies and Research, Issue 18, September, 2021, pp. 57-81.