Journal of Medical Education Development, 2018, Vol 11, No 30, 4 - 21
http://zums.ac.ir/edujournal/

Zanjan University of Medical Sciences

Assessment of construct validity questionnaires in psychological and educational research: Applications, Methods, and Interpretation of Exploratory factor analysis

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Article Info

Article Type:
Review Article

Article history:
Received 2 Mar 2018
Accepted 13 Aug 2018
Published 23 Oct 2018

Keywords:
Psychometrics
Construct Validity
Factor Analysis
Questionnaire
Health Education

Abstract
An important part of studies on psychology of behavior and learning, as well as social and health sciences requires the use of researcher-made questionnaires. To achieve valid results and provide the possibility of publishing the results of a research, researchers seek suitable methods to assess the validity of research tools. This is mainly due to the fact that failure to provide such an important feature in a research tool might lead to the waste of effort and resources allocated to the study. One of the conventional types of validity of measurement tools is construct validity, which is often assessed as one of the most valid statistical techniques using factor analysis method. Generally, factor analysis applies statistical processes to simplify the related measurements and discover a pattern from a group of variables. This method is mainly used to find the simplest way to interpret the observed data. In several fields, including behavioral sciences and psychology, social sciences, medical sciences and nursing, economics, and geography, factor analysis is used as one of the important achievements of technology advancement in computers. In the present research, stages and methods of exploratory factor analysis are discussed and described step-by-step by using SPSS.

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This article is referenced as follows:

Vakili M M. Assessment of construct validity questionnaires in psychological and educational research: Applications, Methods, and Interpretation of Exploratory factor analysis. J Med Educ Dev. 2018; 11 (30) :4-19

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

Introduction

The concept and importance of validity assessment psychological tests are still not completely comprehended. Before the distribution and use of a test, it is essential to determine which qualitative aspect of the questionnaire must be evaluated (1). The term "validity" is one of the most important components of assessment and measurement tools (2, 3), which shows the purpose for which the tool is designed. In fact, validity indicates the ability of the tool to accurately evaluate something that is supposed to be measured. To better comprehend the concept of validity, we need to point out its four types applied in various studies, each with its specific interpretations and features.

The proposed categorization for validity include predictive, concurrent, content, and construct validity. It is worth noting that the predictive and concurrent validities are mutually considered as criterion-oriented validation (1). In criterion-oriented studies, the researcher is primarily interested in the presentation of the criteria that are intended to be predicted. In this regard, in addition to performing a test and obtaining the independent criteria related to a specific topic, researchers calculate the correlation between the criteria as well. If the desired criterion is acquired sometime after the test, the study will be of predictive validity type. In these studies, the main objective is to determine how much a tool is able to predict a specific consequence in the future (1, 4). If the scores derived from a scale are simultaneously measured and compared to the scores of a particular criterion, the research is of concurrent validity type. Generally, concurrent validity is assessed when the purpose is replacing a test with another one (1). Usually, content validity defines and expresses a whole set syllogistically and based on the opinion of a group of experts using a coherent sample of tools (5-8).

The concept of construct validity is regarded when a test is applied to assess some high-quality features that are not operationally defined (1). It is not possible to estimate and correct the destructive effects of random errors and variances of the methods without assessing the construct validity, which could lead to the obtaining of conflicting results (9). A problem faced by researchers is to determine which construct is able to estimate the changes in a functional test. Given the importance of construct validity in measurement tools and questionnaires and incremental measurement and application of factor analysis methods in various sciences of psychology, social, educational and especially health sciences, this study aimed to express the applications, methods, and

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

interpretation techniques for the results obtained from exploratory factor analysis (EFA).

Definition of Factor Analysis

Generally applied to discover a pattern of a group of variables, factor analysis uses statistical processes to simplify the assessments related to each other (10). In fact, the main objective of factor analysis is to find the simplest data interpretation method. The history of factor analysis dates back to the early 1900s and studies by Charles Spearman in the area of humanities, which has led to the development of two factor theories. Historically, factor analysis was first applied by educational researchers and psychologists as a method to interpret self-report questionnaires. Currently, factor analysis is used in various areas, including behavioral sciences and psychology, social sciences, medical sciences and nursing, economy, and geography as a technological advancement in computers (10, 11). In addition, factor analysis is considered as one of the most variable techniques for determining the validity of tools, especially those measuring psychological characteristics. Generally, factor analysis seeks the detection of basic variables or factors in order to explain the correlation pattern between the observed variables.

It should be noted that factor analysis is not a separate statistical method. In fact, it uses a group of statistical analyses, which have a similar role in terms of methodology and function. The variety of theoretical and mathematical concepts among the processes of factor analysis enables the adapting of the analyses to the extent of the study objectives and theoretical foundations of the research. In this way, the results of the research can be used appropriately among a wide range of criteria and tools. At the same time, the flexibility of statistical methods in factor analysis allows the continuation of debate in theapplicationsandmethodsinthisregard (12).

Applications of Factor Analysis

While factor analysis test is often used in studies on social sciences, psychology, and behavioral and educational studies with the aim of evaluating the factors or dimensions of tests and measurement questionnaires, this method is increasingly used in health-related studies such as medicine, nursing and various health trends today. Regardless of which branch of science the research is performed in, a wide range of choices and decisions are available to the researcher in this method to increase the accuracy of factor analysis. By doing so, the researcher can improve the quality of results and solutions of the study. Developing theories

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

and assessing the validity of the test scores have both a close relationship with factor analysis. Factor analysis simultaneously evaluates the accuracy and integrity of the tests and leads to the refinement of most theories. Factor analysis can be used to determine which one of the theoretical constructs is associated with a set of specific data and to what extent these structures can express the main variable of the study (13). In order to achieve the best performance from factor analysis, the following issues must be considered first (12):

1. How large the sample size must be to produce reliable factor analysis results?
2. What is the difference between component analysis and the analysis of shared factors?
3. Is the primary factor rotation matrix pattern necessary to achieve meaningful and interpretable results?

In tool designing studies, three important goals of using factor analysis as a multivariate statistical method are considered by researchers (14), as follows:

1. Reducing the number of variables or items to shorten the tool
2. Identifying the relationships between factors of infrastructure structures and recognizing and shaping latent structures based on scientific theories and/or re-refining them
3. Providing documentation related to the validity of self-reporting scale structures

Factor Analysis Types

Factor analysis is divided into two major groups, including exploratory (EFA) and confirmatory (CFA) factor analyses (10, 11). Since the initial development of factor analysis from more than a hundred years ago, EFA has been one of the most widely used statistical methods in psychological research (15). In general, EFA is applied in the first step of constructing a scale or a new measuring instrument. The purpose of EFA is to identify complex patterns through the discovery of coherent data and prediction tests. This method allows the researcher to detect the main dimensions fitting the theory used in the research from a relatively large number of latent structures, each of which is often expressed by a list of items and can be reduced to less common groups. On the other hand, CFA is an attempt made to confirm the research hypotheses and apply a path analysis diagram to describe the variables and factors (10). In using CFA, the researcher usually has a predetermined or expected expectation of the model structures, which is used to test the proposed theory in the research. In addition, CFA aims to determine which of the proposed factor structures is more appropriate regarding the theory of the research (14).

Considering the high application of EFA in construct validity evaluation, the present study was conducted to introduce the EFA and its stages using SPSS.

Basic Steps of Structural Validity Evaluation by EFA

Perhaps more than other commonly used statistical methods, the use of EFA requires that the decision-making of researchers on some aspects of data analysis via this method. In this respect, there are at least five major methodological issues that must be considered by a researcher during the performing of factor analysis. First, the researcher must decide on the variables and the size and nature of the samples studied in the research. Second, the researcher should determine whether, according to the objectives of the study, the EFA is the most appropriate method of data analysis or not. Third, assuming that EFA is a suitable method, a proprietary process must be selected to adapt the model or theoretical model based on the type and nature of the data. Fourth, the researcher must decide on the number of model factors, and fifth, the researcher must select a suitable method of primary factor rotation to achieve a simpler solution to result interpretation (15).

Despite the fact that EFA seems to be a complex statistical approach, it is based on continuous and linear approaches and has the ability toutilize many options. Therefore, thedevelopment of aninstruction or a specific pathway to use EFA is a crucial potential in appropriate decision-making. A guide to conducting factoranalysis has been presented in five distinct and sequential stagesinFigure 1. The researchers' compliance with this guideline can provide a clear path for clear decisions (14). All five stages along with theirnecessarydetailsarepresented below.

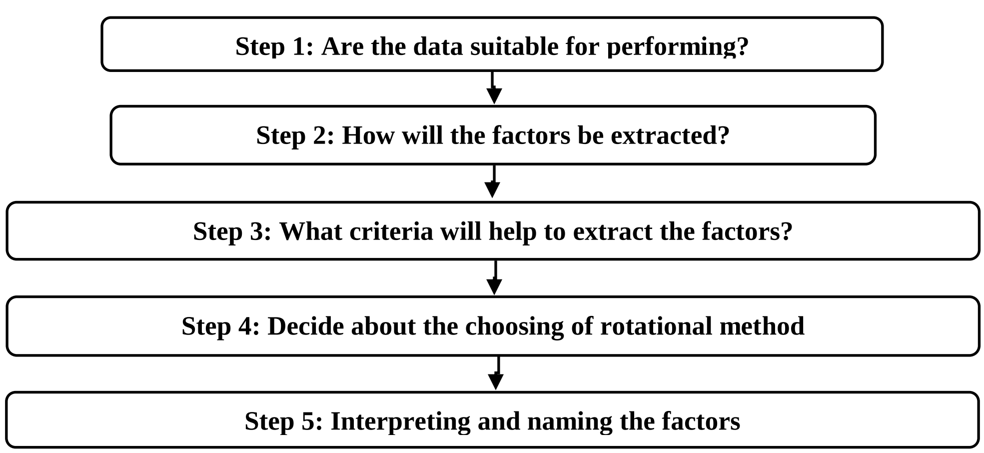

Figure 1: Five Basic Steps for Exploratory Factor Analysis (14)

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

Step 1: Are the data suitable for performing?

Sample size: in reviewing the literature related to factor analysis, much attention has been paid to the issue of sample size. It is widely accepted that the use of larger sample sizes in the application of factor analysis leads to a more accurate estimation of the trait studied in the population, resulting in more stable results (16). The first question raised in the first step in the design of factor analysis is how large the sample size should be to obtain valid results (12, 16). The researcher should determine how large the sample size is and how the required sample is to be selected from the population under study. Experts have suggested different methods to determine the appropriate sample size. Most sample size guides propose larger sample sizes based on the number of variables measured in the analysis. At the same time, sometimes such guides suggest minimum sample sizes regardless of the number of variables tested (15). Unfortunately, it should be acknowledged that these guides have serious problems, including the considerable difference in the sample size recommended in these guides. Nevertheless, there is a global agreement on this issue that the inadequate sample size can affect the process of factor analysis and produce invalid results (17). In reviewing the literature, there is a large amount of information available to answer this question. However, the criteria used to determine the sample size for factor analysis are very different and cover a wide range (14). Decision-making criteria for the appropriate sample size can be divided into two categories (17):

1. Determining a Minimum of Items or Subjects:

In terms of sample size required for factor analysis, there are different opinions and several criteria have been provided in scientific sources. The proper minimum number of participants has been reported differently by researchers in different researches. For instance, Lawley and Maxwell introduced the sample size to be equal to the total number of items plus 51 participants (12). Other researchers, including Suhr and Hair, Sofroniou & Hutcheson, Gorsuch, and Tabachnick and Norušis proposed minimum sample sizes of 100, 150-300, 200, and 300, respectively (14). In addition, Lee and Comrey presented the proper sample size in factor analysis as a ranked scale: 100 (significantly weak), 200 (relatively good), 500 (significantly good), and ≥1000 (excellent) (12).

2. Determining a Sample Size and the Number of Studied Variables:

The second method proposed by researchers to determine the appropriate sample size is given according to the criterion that how many participants are required per variable or item, commonly known as sample to variable ratio (N:P), N being the number of participants and P being the number of variables. A rule of thumb is a range of ratios, including 3:1, 6:1, 10:1, 15:1, and 20:1. Gorsuch proposed 5:1 ratio and emphasized that sample size must not be less than 100 individuals (15). On the other hand, Yarnold and Bryant proposed 10:1 ratio and emphasized that this ratio must not be less than five. Moreover, Suhr proposed a minimum of 5:1 ratio (18). Nevertheless, MacCallum marked that the rule of thumb is not that reliable and determining a suitable sample size depends on other dimensions of the research design (19). However, in case of equality of other aspects, larger sample sizes are more suitable than smaller ones. This is mainly due to the fact that larger sample sizes tend to reduce the probability of error and increase the accuracy of population estimation while enhancing the generalizability of the results (17).

Despite this variation and controversy, one can conclude that almost the majority of studies have reported a minimum ratio of 5:1 and a maximum of 10:1. Therefore, if an evaluated scale contains 30 items, the appropriate sample size can vary between a minimum and a maximum of 150 to 300 people.

Sampling Adequacy Criterion of Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity:

In EFA, another method is proposed to evaluate the adequacy of the sample size known as Kaiser-Meyer-Olkin (KMO). In order to perform the EFA order in SPSS, we need to first select the item of “Factor” by clicking on the item “Dimension Reduction” through the menu of “Analyze” (Figure 1). After that, the studied variables must be selected in order and transmitted to the mentioned section. Before the extraction of tool factors, some tests must be performed to evaluate the suitability of the data or responses of participants. These tests include KMO and Bartlett's test of sphericity. In order to perform this part of EFA, first we need to click on “Descriptive” and then select the “KMO” item. Exclusive estimation of KMO indicator is recommended when the subject to variable ratio of the research is less than 5:1. This index measures the values between zero and one, and values greater than 0.50 indicate that the sample size is sufficient to perform the factor analysis, and KMO values smaller than 0.5 show that the correlation between pairs of variables is not adequately explained by other variables, so the application of the factor analysis method is not appropriate. If the KMO value is between 0.5 and 0.69, it is advisable to use factor analysis with caution, but values greater than 0.7 indicate that the correlation between the data is suitable for performing factor analysis.

(14). Furthermore, the Bartlett's test of sphericity must have a significance level below 0.05 in order to apply the factor analysis (20).

Table 1: First Output Exploratory Factor Analysis for Sampling Adequacy by Kaiser-Meyer-Olkin (KMO) Method and Bartlett Test: (Interpersonal Communication Skill Assessment Tool) (20)

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.778
Bartlett's Test of Sphericity	**Approx. Chi-Square**	1316.347
	df	465
	Sig.	0.000

Factorability of Correlation Matrix

In order to perform the factor analysis, there must be a correlation matrix between each of the variables of the tool. Tabachnick emphasized that the coefficient of correlation matrix (which if often presented as R factorability) must be at least 0.30. The 0.30 factorability of variables shows that the evaluated factors express 30% of the relations between the data or practically demonstrates that one-third of the variables share over-variance. If the correlation matrix of none of the variables reaches above 0.30, the researcher must determine whether the factor analysis has been a proper statistical method or not. The second output of factor analysis is a table that shows two features, including initial share, the amount of which is equal to one for all items since it expresses the values of factors before extraction (20). The second feature shows the extraction share of the items. In this regard, the larger the size of this variable, the better it is able to show the desired variable. The values of initial and extraction shares are presented in Table 2 for a sample of tool with 33 items. As observed, the extraction share values are above 0.40 for all items, demonstrating the sufficient fit of the tool items for factor analysis. If the extraction load of a variable is below 0.30, it must be removed from the list of items and the factor analysis stages must be re-implemented.

[DOR: 20.1001.1.22519521.1397.11.30.7.6]
[DOI: 10.29252/edcj.11.30.4]

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Table 2: Secondary Output Factor Analysis for Estimating Extractional Shared of Factor of Interpersonal Communication skills Scale Measurement (20)

Items	Initial	Extraction	Items	Initial	Extraction
Item1	1.000	.731	Item16	1.000	.636
Item2	1.000	.732	Item17	1.000	.739
Item3	1.000	.780	Item18	1.000	.736
Item4	1.000	.619	Item19	1.000	.547
Item5	1.000	.613	Item20	1.000	.822
Item6	1.000	.691	Item21	1.000	.777
Item7	1.000	.594	Item22	1.000	.579
Item8	1.000	.821	Item23	1.000	.659
Item9	1.000	.777	Item24	1.000	.768
Item10	1.000	.707	Item25	1.000	.718
Item11	1.000	.668	Item26	1.000	.721
Item12	1.000	.719	Item27	1.000	.586
Item13	1.000	.697	Item28	1.000	.793
Item14	1.000	.700	Item29	1.000	.818
Item15	1.000	.662	Item30	1.000	.770

Second Step: How the Factors Are Extracted?

The purpose of the rotation of the factors is to simplify the factor structure of a group of items. In other words, it is the recognition of items that have a high factor loading or smaller factor loadings that are categorized based on a factor. Various methods exist to extract factors, including (14):

- Principal components analysis (PCA)
- Principal axis factoring (PAF)
- Maximum likelihood
- Unweighted least squares
- Generalized least squares
- Alpha factoring
- Image factoring

In the majority of published studies, use of the first and second methods (i.e., PCA and PAF) is very common. However, decision-making about the necessity of using both mentioned techniques has been deeply discussed by researchers. While no significant difference is found in the results of these two methods in practice, especially when the variables have a high reliability (14), or the number of variables is ≥30, the primary adjustment of relevant software with EFA, including SPSS, is on the first item or PCA. In addition, this method is recommended when the research has not been based on a specific theory.

Third Step: Which Criteria Help Determining the Extracted Factors?

The main goal of data extraction is reducing the number of variables in factors. There are several criteria available to researchers to achieve a uniform scale and simplify the factors. Nevertheless, due to the type of selection and sometimes the confusing nature of some factor analyses, one should not focus solely on a particular criterion

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(14). Thompson and Daniel emphasized that simultaneous application of several decision-making rules, including Kaiser Criterion (consisting of special initial values above one), Bartlett's test of sphericity, the cumulative percentage of extractive variances, and parallel analyses, is appropriate (21).

Cumulative Percentage of Extractive Variances and Rule of Initial Values above One

Cumulative percentage of extractive variances is one of the disputed areas in relation to the factor analysis approach, especially in various sciences (e.g., experimental sciences, psychology, humanities). While various percentages have been suggested by experts, there is absolutely no limit to this area. According to the opinion of Hair et al., the number of selected factors should be stopped when the cumulative percentage of variances reaches at least 95% in experimental sciences. However, the expressed value of variance in humanities often varies in the range of 50-60% (14). As observed, the number of rows in the table is equal to the number of variables or items of the tool. For instance, if a tool contains 33 items, the number of created rows will be equal to 33.

Table 3: Third Output of Exploratory Factor Analysis for the Estimation of Total and Cumulative Variances of Extractive and Predictability of Instrument: (Initial Eigenvalues Values and Extractive Extraction and Rotation Sums of Squared Loadings of Interpersonal Communication Skill Measurement Tool)(20)

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	8.750	30.173	30.173	8.750	30.173	30.173	3.910	13.482	13.482
2	2.507	8.644	38.817	2.507	8.644	38.817	3.192	11.008	24.490
3	2.439	8.410	47.227	2.439	8.410	47.227	2.955	10.188	34.678
4	1.874	6.461	53.688	1.874	6.461	53.688	2.616	9.019	43.698
5	1.745	6.017	59.704	1.745	6.017	59.704	2.451	8.453	52.150
6	1.301	4.488	64.192	1.301	4.488	64.192	2.373	8.184	60.335
7	1.240	4.276	68.468	1.240	4.276	68.468	2.359	8.133	68.468
8	.909	3.136	71.603						

Extraction Method: Principal Component Analysis.

Scree Plot or Pebble Test

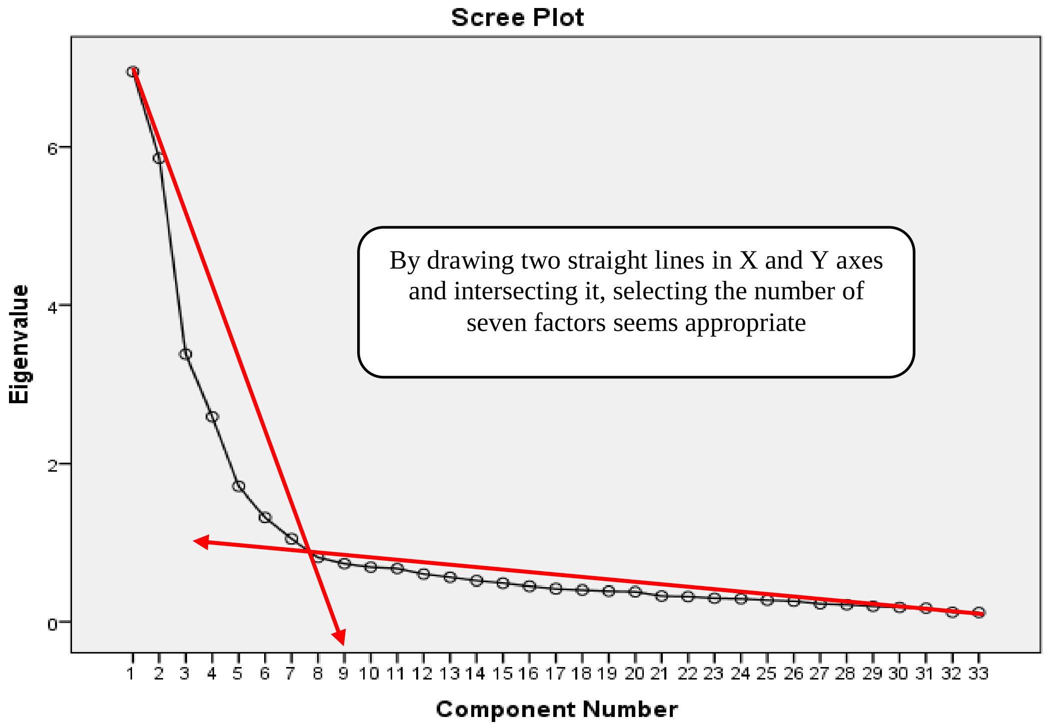
The pebble test is a type of visual expression of factors and their relevant special initial values, interpretation of which requires the judgement of researchers (12, 14). The Scree plot was designed by Cattell and received this name due to its similarity to rock pieces on hillside (14). The X axil or pebble, factors or tool components, and the axis of y show the special initial values. Since the first factor calculates most amount of changes, it has the highest initial value as well. The values of the initial value decrease in succession, and therefore, the diagram is formed in a shape similar to the elbow of the hand. Deciding on the cut-off point of the chart is completely subjective and requires attention to a number of factors, including the amount of initial values and extracted factors (12, 22). In addition, deciding which of the factors should be preserved is often controversial and leads to ongoing debates on this issue. However, such a controversy declines with the increase in sample size. The main question is that at which point the breaking occurs? Evaluation and interpretation of this curve consist of two stages:

1. Drawing a straight line from the smaller values of the initial value and its extension to the point where it moves out of the curve. By drawing such a line, the mentioned line will be separated exactly at the breaking point.

2. The points that are separated or broken above the line indicate the number of factors that need to be preserved. In Diagram 1, it is observed that the first six factors have the highest ability to predict the evaluated variable, and no significant increase occurs by selecting the factors from number seven onward. In Figure 6, we can see the number of extracted factors and the initial value of the nursing communication skills tool (20).

By drawing two straight lines in two vertical and horizontal axes, and considering the intersection of the two lines, it seems appropriate to select a number of seven factors with an initial value higher than one. However, in order to make a final decision, the amount of changes that can be expressed by each of the factors and the way the items are placed in each of the seven factors must be considered. It is often more difficult to decide on selecting the last factors because they have less initial value and variance predictive power. By selecting a greater number of factors, the power of the tool in predicting the changes in the trait studied should be significantly increased. In Figure

6, seven factors with an initial value above one are identified by observing the intersection of two straight lines. However, by passing other factor analysis stages and considering the distribution of items in these factors and their factor loading and comparing the power of six and seven factors in predicting the traits of the study, the selection of six first factors is sufficient and appropriate for evaluation.



Graph 1: The number of suitable factors for selection using the Scree Plot (20)

Fourth Step: Selection of Rotational Methods:

Another issue that must be considered when deciding on the number of factors is that the data or variables are associated with one or more factors. Using the rotation statement, the variables with the highest and lowest factor loadings are identified, which simplifies the process of selecting and interpreting the factors. There are two conventional methods for variable rotation, including orthogonal rotation and oblique rotation. In both methods, researchers have several selection methods, including oblique olbimin/promax and orthogonal varimax/quartimax. From the mentioned methods, the orthogonal varimax is the most conventional technique in factor analyses.

In contrast, the oblique rotation creates interconnected factors and produces a higher rate of accurate results in studies on humanities. The same is observed when data is not compatible with previous assumptions. Regardless of which rotational

[DOR: 20.1001.1.22519521.1397.11.30.7.6]

[DOI: 10.29252/edcj.11.30.4]

method is used, the main purpose is presenting the results with a simpler interpretation and production of cost-effective solutions. Experts recommend the use of both PCA and PAF methods to compare and efficiently evaluate the results since each of the methods used for rotation of factors presents the best and most appropriate factors and selecting more favorable results requires the evaluation and comparison of results both visually and conceptually. Occasionally, a single item may have a high factor loading in a number of factors simultaneously, or is not in any of them, or its meaning is not logically fit to the related factor structure. Therefore, after performing this stage of factor analysis process, the researcher must focus on the evaluation of the aforementioned cases, including those factors that have low factor loadings or are not placed in selected factors or lack the appropriate fit, and decide whether they have to be removed or not (14, 23).

Fifth Step: Result Interpretation:

Interpretation is related to the researcher's assessment of which of the variables are related to the factor, and the names to be selected for the factors. For instance, in a study in the field of nursing or medicine, a specific factor with five variables or items may all relate to the concept of pain perception, which could lead to the selection of “pain perception” name for the factor by researcher. Traditionally, a factor must include a minimum of three variables with appropriate factor loading in order to provide a meaningful and comprehensible interpretation. The naming of factors is an abstract, theoretical, and deductive process. However, signifying the latent extracted factors ultimately depends on the definition by the researcher. In other words, it is possible that some factors describe a large response together in a research. The fifth output of EFA related to the rotated matrix of components or factors is shown in Table 4. By considering the extracted rotational loadings of factors or variables of the tool, we could easily identify how they are located in each factor. Components or variables that have the minimum acceptable factor loading of 0.40, and consecutively or dispersedly establish a group or cluster, will constitute one of the factors or structures OF the research tool together.

In using factor analysis, it is important to pay attention to this issue that researchers must be able to independently evaluate the results obtained by EFA (13). Such an assessment should be carried out at two levels; firstly, given the uncritical decisions

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that are made in EFA, other independent researchers should be able to evaluate the analytical choices reported by the author. Secondly, independent researchers must be able to re-implement the study with new data or even use the CFA. However, re-execution of the study with CFA method must be carried out using a new sample. Replication of the study by CFA method using the same data that was exploited in EFA is not appropriate at all and can be highly misleading (13).

EFA Limitations

As mentioned earlier, the researcher should consider five major methodological issues in using EFA. If all of the above issues are not equally provided by the researcher in a research, EFA may lead to poor results (15). At the same time, one of the limitations of EFA is the problems associated with selecting the names of the factors. The names of factors may sometimes not accurately reflect their internal variables. Moreover, sometimes the interpretation of some variables is difficult because they may be located in more than one factor (10).

Sometimes the dispersion of the factors may not be consistent with the theoretical framework desired by the researcher. In the event of a researcher encountering such conditions, he must act operationally so that the name selected for the factor could reflect the theoretical and conceptual objectives of the research. For instance, one of the commonly used health education models to study the preventive behaviors of AIDS is the “Health Belief Model”, which has five main structures (24). Suppose that in using this model, factors that could have been classified as "perceived barriers" under one factor are placed in two separate factors (e.g., factor number five with three items and factor number six with four items) by EFA. Meanwhile, it might be appropriate to select two separate names that are at the same time related to the theoretical framework used in the research (e.g., perceived individual barriers and perceived educational barriers). Such naming can be carried out by taking into account the concept and content of a set of clauses that are located in one factor, as well as according to the expert opinion. Therefore, decision-making on selecting and naming of factors are also dependent on the opinions of the research team and should not solely based on the results of factor analysis. In SPSS, there are options to decide on the number of extracted factors and to determine the minimum values of acceptable factor loadings, selection of each of which enables researchers to form new results and outputs and compare them with each other. By doing so, it would be possible to make the best decisions by combining all the results from factor analysis, theoretical foundations, similar studies, and the experiences and intentions of the research team. The next major limitation of EFA is that the researcher is required to manage the study using a large volume of samples at a given moment of time to ensure the reliability of the factors (10).

Table 4: Fifth Output Exploratory Factor Analysis: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization (interpersonal communication skills (20) Rotated Component Matrix[a]

Items	Component						
	1	2	3	4	5	6	7
General skill 1	.801	-.064	.047	.229	.007	-.018	.156
General skill 2	.765	.254	.048	.088	.175	.180	.089
General skill 3	.724	-.064	-.043	.250	.051	.338	.269
General skill 4	.765	.090	.051	.090	-.001	.112	.106
General skill 5	.592	.118	.061	.275	.147	.199	.029
General skill 6	.576	.322	.101	.174	.222	.364	-.200
Speaking skills 1	.303	.390	.201	.508	.094	.209	-.115
Speaking skills 2	.233	.173	.181	.793	.119	.202	.111
Speaking skills 3	.270	.166	.329	.739	.055	.053	.045
Speaking skills 4	.113	.136	.134	.787	-.111	.018	.143
Active listening skills 1	.265	.704	.245	.040	.088	.100	.029
Active listening skills 2	.040	.738	.146	.270	.136	.220	.123
Active listening skills 3	.078	.637	.314	.279	-.111	-.037	.225
Active listening skills 4	-.067	.766	-.111	.123	.112	-.013	.176
Message Interpreting skill 1	.130	.219	.631	.120	.039	-.014	.321
Message Interpreting skill 2	.091	.295	.678	.186	.162	.072	.012
Message Interpreting skill 3	-.161	-.101	.769	.133	.139	.164	.202
Message Interpreting skill 4	.102	.183	.716	.228	-.051	.150	-.050
Asking skill 1	.186	.288	.056	.085	.270	.136	.485
Asking skill 2	.307	.239	.083	.103	.104	.074	.782
Asking skill 3	.093	.078	.117	.089	.178	.010	.836
Asking skill 4	.109	.196	.184	-.011	.268	.060	.729
Feedback 1	.195	.204	.174	-.131	.734	-.037	-.086
Feedback 2	.158	.202	.218	-.056	.772	-.142	.157
Feedback 3	-.078	-.133	-.033	.089	.717	.243	.339
Feedback 4	-.018	-.008	-.096	.268	.673	.188	.156
Audience encouraging Skill 1	.134	.045	.519	.214	.107	.485	-.155
Audience encouraging Skill 2	.201	-.111	.274	.087	.082	.761	.218
Audience encouraging Skill 3	.225	.256	.073	.144	-.030	.817	.006
Audience encouraging Skill 4	.342	.476	.210	.034	.106	.589	-.014

[DOR: 20.1001.1.22519521.1397.11.30.7.6]
[DOI: 10.29252/edcj.11.30.4]

Conclusion

Today, by expanding the tools and measures of measuring abstract concepts and variables (e.g., attitudes and beliefs related to health) and necessity of evaluating the psychological consequences of clinical and counseling and educational interventions, attention to the issue of tool validity has been turned into an important and critical issue for researchers. Currently, an important part of the research conducted in different branches of psychology, social sciences, education and various trends related to health sciences, which are conducted with descriptive, analytical or interventional purposes, requires the use of researcher-made tools.

As a result, researchers are interested in using appropriate methods to evaluate the validity of research tools in order to obtain valid results and provide the possibility of publishing the results of the research since failure to provide such an important feature in the research tool may lead to the loss of efforts and resources allocated to study. One of the most important types of validity of measurement tools is construct validity, one of the most valid and most common methods for evaluation of which is factor analysis. In the present study, attempts were made to discuss and describe the stages and methods of this technique step-by-step and using the SPSS. This method enables researchers to eliminate the inappropriate items from the designed tool in order to shorten the questionnaire and at the same time recognize the factors with the ability to properly predict the studied variable. It is suggested that more attention be paid to basic topics in the methodology of medical sciences research and other research fields. Today, one of the most important criteria affecting the acceptance or lack of acceptance of research findings in valid foreign and domestic journals is the quality and method of provision of documentations related to the assessment of reliability and validity of research measurement tools. While more extensive discussions could be made on this method, it is hoped that the results of the present study would be useful to other researchers.

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