Comparison of Common Methods of Extraction and Rotation in Exploratory Factor Analysis to Validate the Addiction Potential Questionnaire of 12-18-Year-Old Iranian Children

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Abstract- The drug crisis, especially in children, is expanding as a global challenge. The purpose of this study was to compare extraction and rotation methods in exploratory factor analysis to validate the children's addiction potential questionnaire. This cross-sectional study was conducted in 2023 on 400 students from the city of Shiraz, Iran, using a multi-stage sampling method (stratified-cluster-simple random sampling). Inclusion Criteria: Participants were students residing in Shiraz and enrolled in the first or second year of high school. After designing the questions and assessing their face and content validity, as well as reliability (using Cronbach's alpha), the final questionnaire was administered to the participants. Exploratory factor analysis was performed using various extraction and rotation methods. The statistical methods used for analysis included descriptive-analytical indices, correlation coefficients, exploratory factor analysis, and Cronbach's alpha, utilizing SPSS software version 26. This research has received ethical approval under the code IR.SUMS.SCHEANUT.REC.1402.112. The mean age of participants was 15.39±1.94 years. The face and content validity (both quantitatively and qualitatively) as well as reliability (using Cronbach's alpha) were assessed and confirmed. The best extraction method was maximum likelihood, and the optimal rotation method was Varimax. The percentage of variance explained varied across different extraction methods, with the highest percentage being 39.5% for the Generalized Least Squares method and the lowest percentage being 25.8% for the Image Factoring method. The results indicate a suitable validation of the children’s addiction potential questionnaire. The careful selection of extraction and rotation methods based on the characteristics of the data and the research objectives plays a crucial role in achieving valid results. In this study, the best extraction method was found to be maximum likelihood, and the optimal rotation method was Varimax, resulting in the identification of four factors.

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Introduction

The drug crisis is one of the major challenges facing the world, exacerbating addiction as a growing social issue (1,2). The United Nations defines addiction as an acute or chronic intoxication that is harmful to both individuals and society (3,4). The decreasing age of addiction in Iran indicates the vulnerability of this segment of society to drugs, making it essential to examine the phenomenon of children's addiction as a critical issue in today's society (5-8). The 2022 United Nations report indicates a 26% increase in drug consumption globally over the past decade (9).

However, one of the main challenges in addiction-related research is the lack of standardized tools to measure children's addiction potential (10-12). In this regard, researchers initially conducted a systematic study (3) that revealed many existing tools face limitations in their validation processes, which may prevent them from accurately reflecting the specific needs and characteristics of children (5,10-41). Therefore, the design of new tools for assessing potential for addiction in this group is essential (3,6,42).

After designing the tool, it is essential to first evaluate and confirm its face and content validity both quantitatively and qualitatively (43-49). Face validity refers to whether the questionnaire items clearly reflect the intended concept, while content validity addresses whether all aspects related to children's potential for addiction are included in the tool (44-46,48,49). Additionally, the reliability of the instrument must be assessed to ensure that its results are repeatable and valid (45,46,48-52). Following this, construct validity is measured through exploratory factor analysis (EFA). EFA is a statistical technique used to identify underlying structures in data and reduce their dimensionality (46,48, 49,53,54). The exploratory factor analysis process consists of two key stages: factor extraction and factor rotation (45,46,48,49,55-61). Extraction involves determining the minimum number of factors that can be used for the best representation of the intercorrelation among variables. The most common methods include: least squares, generalized least squares, maximum likelihood, principal axis factoring, alpha factoring, and image factoring (45,46,48,49,55-64). Furthermore, rotation is a process used to adjust the factor axes to achieve simpler and more interpretable factors, making the output more comprehensible (46,48,55-62,64). Rotation methods are categorized into orthogonal (e.g., Varimax, Quartimax, Equamax) and oblique (e.g., Promax and Direct Oblimin) methods (46,48,57-61,63-65).

Considering the abundance of theories, hypotheses and various complexities in the field of children's addiction (66-75), as well as the mentioned cases, which method of extraction and rotation should be used, there were many sources and opinions (46,49,52,54,57-60,62, 64,65,71,76-79). In the current research, various methods of extraction and rotation in exploratory factor analysis were investigated and compared in order to validate the children's addiction potential questionnaire. Considering the importance of this issue in health science research, detailed analysis of these methods can help improve the quality of measurement tools and ultimately lead to a better understanding of the phenomenon of addiction in children.

Materials and Methods

It was a cross-sectional study that was conducted in 2023 in the city of Shiraz (Iran). The initial steps of formulating questions according to the opinion of experts, review of texts, supervisors, review of questionnaires with these concepts were carried out and the pool of items was formed and then related questions were designed. After the finalization of the questions, face validity was assessed quantitatively and qualitatively by 32 participants and 15 experts, and content validity was assessed qualitatively and quantitatively by 15 experts. Reliability was also evaluated through Cronbach's alpha. In the next step, different methods of extraction and rotation were compared and evaluated with exploratory factor analysis. In this research, different combinations of these methods (according to the following formula, 6 extraction methods, 5 rotation methods plus Direct Oblimin and Promax rotation with three different cutoffs that formed 9 rotation methods and 8 factors obtained from the output of the software were combined. A total of 432 permutations formed) from the same dataset and similar variables (including age, gender, academic year, educational level and educational district) were compared and investigated. Formula: $n1*n2*n3=6*9*8=432$

In this way, for analysis, each of the different extraction methods was fixed and with different types of rotations for each analysis factor. For example, select the Maximum Likelihood method, select the number of factors as 1, and in the rotation tab; We analyzed different rotations: Varimax, Quartimax: Equamax, Promax and Direct Oblimin.

The sample size according to scientific principles (46-49,52,54,57-59,62,64,65,76-79), after determining the number of questions (final 30 questions), taking into account the possible loss of participants, 400 people were considered. The study population consisted of children aged 12 to 18 years old in Shiraz city and the research sample consisted of students aged 12 to 18 years old in schools in Shiraz city, who were selected by multi-stage sampling method (stratified-cluster-simple random). The city of Shiraz was divided into 4 strata based on the 4 areas of education and based on the total volume required, the sample size was calculated in each stratum. Then, within each strata as a cluster from the list of schools in the last strata, the required number of schools were selected by simple random and then the required number of students were selected by simple random in each school. Inclusion criteria: students, residents of Shiraz, studying in the first or second year of high school, students who were willing to cooperate in the study.

In order to keep the information confidential, no names and addresses were recorded on the questionnaires. Statistical methods for analysis were descriptive and analytical indices, Pearson's correlation coefficient, exploratory analysis factor, Cronbach's alpha. SPSS version 26 software was used. This research was approved by the Ethics Committee of Shiraz University of Medical Sciences (IR.SUMS.SCHEANUT.REC.1402.112). Verbal consent was also obtained from each participant and the participants were assured that cooperation in the research is voluntary.

Results

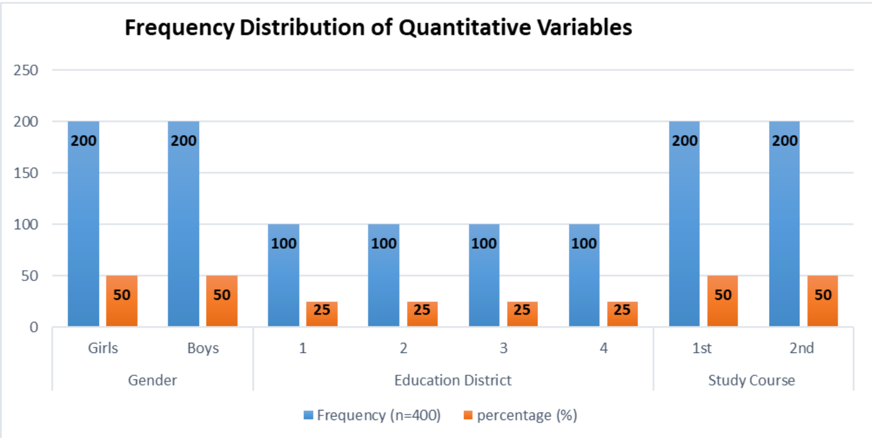
Descriptive results

There were 400 students who were in the age range of 12 to 18 years (average age 15.39±1.94 years) (Table 1), 200 (50%) of the participants were girls. The number of students in each district was 25% (Graph 1).

This Graph illustrates the frequency distribution and percentage of participants categorized by gender, educational district, and study course.

Table 1. Descriptive Statistics of Age

Quantitative variable	Mean±SD	Min	Max
Age	15.39±1.94	12	18



Graph 1. Frequency Distribution and Percentage by Gender, Educational District, and Study Course

Items generation

By reviewing scientific texts, theories and hypotheses, existing questionnaires and experts' opinions, 30 final items were compiled.

Face validity

Quantitative face validity showed that all the items had an acceptable score higher than 1.5 (46-49,58,59,62,80) in terms of importance. Also, in the qualitative part, the items were modified by experts and participants; After measuring the face validity, the reliability of the questions was confirmed with Cronbach's alpha of 0.87.

Content validity

In the qualitative part, the items of the questionnaire were modified according to the opinion of experts, and in the quantitative part, the values of the content validity ratio (CVR>0.49) and the content validity index (CVI>0.79) were acceptable (47,58,59,62,80).

Construct validity

It was done through exploratory factor analysis. All assumptions (sample size, data normality, outliers, missing data, correlation between items, collinearity, factorability and sampling adequacy) were established (46-48,58).

According to Table 2, the questions were factorable (KMO=.088) and adequate to extract and explore factors (Bartlett's sphericity test was significant (*P*<0.0001)) (46-49,58,59,62).

Table 3 shows the results of different extraction methods and types of rotation in the Minimum Communality. The minimum coefficients related to Image factoring (IF) method was 0.10 and the maximum coefficients related to Generalized least squares (GLS) method was 0.27 and then Maximum Likelihood (ML) was 0.20 (Table 3).

Table 4 shows the results of different extraction methods and types of rotation in the maximum Communality (Table 4). The minimum coefficient related to the IF method were 0.43 and the maximum communality coefficients related to the GLS method were 0.62 and then ML with 0.57.

Table 5 shows the percentage of total variance explained in extraction and rotation methods. As can be seen, different rotations in each extraction method do not change the percentage of total variance, but it is the extraction method that changes the percentage of variance explanation. The minimum percentage of total variance related to IF method was 25.8% and the maximum percentage of total variance explained was related to GLS with 39.5% and then ML (37.9%).

Table 2. The result of the KMO statistic and Bartlett's sphericity test

Indicators	Amount
KMO statistic and Bartlett's sphericity test	0.88
Chi-square statistics	2846.484
Degrees of freedom	435
p	*P*<0.001

Table 3. Minimum communality in different extraction methods and types of rotation

Factor Extraction	Factor rotation technique/communality minimum								
	Varimax	Direct oblimin			Quartimax	Equamax	Promax		
		0	-2	+0.8			2	4	6
Unweighted least squares	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Generalized least squares	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
Maximum likelihood	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Principal axis factoring	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Alpha factoring	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Image factoring	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

Table 4. Maximum communality in different extraction methods and types of rotation

Factor extraction	Factor rotation technique/ communality maximum								
	Varimax	Direct oblimin			Quartimax	Equamax	Promax		
		0	-2	+0.8			2	4	6
Unweighted least squares	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Generalized least squares	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62	0.62
Maximum likelihood	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Principal axis factoring	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54
Alpha factoring	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Image factoring	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43

Table 5. The percentage of total variance explained in different methods and types of rotation

Factor extraction	Factor rotation technique/total variance explained								
	Varimax	Direct oblimin			Quartimax	Equamax	Promax		
		0	-2	+0.8			2	4	6
Unweighted least squares	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%
Generalized least squares	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%	39.5%
Maximum likelihood	37.9%	37.9%	37.9%	37.9%	37.9%	37.9%	37.9%	37.9%	37.9%
Principal axis factoring	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%	37.5%
Alpha factoring	37.4%	37.4%	37.4%	37.4%	37.4%	37.4%	37.4%	37.4%	37.4%
Image factoring	25.8%	25.8%	25.8%	25.8%	25.8%	25.8%	25.8%	25.8%	25.8%

The number of extracted factors according to the default of the software (Eigenvalue> 1) was the same in extraction and rotation methods and 8 factors were reported in all models. In the next step, the number of extraction factors was changed from 1 to 8 manually in the software for different extraction and rotation methods, which resulted in 432 combinations. By placing different factors, the same results were reported.

Discussion

In this research, it was investigated and compared the common methods of extraction and rotation in exploratory factor analysis to validate the potential tool for children's addiction. According to the results, all the items were acceptable in terms of face and content validity quantitatively and qualitatively. Also, in terms of reliability, the value of Cronbach's alpha was 0.87. The results of the exploratory factor analysis showed that all the necessary assumptions were met. The results of the KMO test (0.88) and Bartlett's sphericity test (P<0.0001) indicated the adequacy of sampling for factor analysis. The main findings showed; The minimum and maximum coefficients in the lowest and highest communality of the items were related to the IF method and the GLS and ML methods, respectively. Also, GLS method with 39.5% and then ML with 37.9% provide the highest variance explanation percentage, while IF method had the lowest explanation percentage with 25.8%. In the current research, the best method of maximum likelihood extraction, the best type of varimax rotation and the best number of factors, 4 factors were considered.

In this study, all assumptions were met and the results of KMO test (0.88) and Bartlett's sphericity test (P<0.0001) indicated the adequacy of sampling for factor analysis. These findings were consistent with the results of other studies that also emphasize the importance of these assumptions (46,48,49,58,59,62,78,79). It is obvious that for any statistical analysis, it is necessary to check the relevant assumptions first, and if the defaults are established, more logical and reliable results will be obtained. The fact that the KMO test and Bartlett's sphericity test were similar for all types of extraction and rotation methods is probably because in all extraction and rotation methods, the initial data were the same (same dataset) and in all methods, similar assumptions were used to perform factor analysis. Therefore, KMO and Bartlett's test are not dependent on the type of extraction or rotation method. They are more influenced by the characteristics of the data than by specific methods of analysis.

The findings showed that different combinations of extraction and rotation have different effects on the amount of communality. The minimum coefficients in the lowest communality were related to the IF method and the maximum coefficients were related to the GLS method and then ML. Also, the minimum and maximum coefficients in the highest communality were related to IF method and GLS method and then ML. In the current study, the GLS and ML methods have the highest coefficients and the IF method has the lowest coefficients, perhaps because it is important to comply with the EFA assumptions, especially normality, no missing data, and no outliers in the GLS and ML method. It has more than other methods, especially IF. In other words, in the present study, the EFA presuppositions were in place, and this has caused the GLS and ML methods to show higher coefficients. Whereas, if the default was not established, the coefficients in the IF method would be expected to be higher. Other studies that investigated these methods are also in line with the present research. Another possible reason is that GLS shows better results when the correlation between items is more than 0.3, and IF is the most appropriate method when the correlation between items is low, which is one of the default assumptions in our study. has been observed. The opinion of experts in this field and other studies confirm this finding. Among other possible reasons, it can be pointed out that GLS is usually more accurate than the IF method and the rest of the methods when we have more complex models and the number of extracted factors is high (46,48,49,60,62,78,79). ML is also one of the methods that, in addition to having characteristics similar to the GLS method, provides more accurate and optimal estimates of parameters due to the use of the maximum likelihood method (46,48,49,57-60,81,82). This feature makes the results of this method more reliable than other methods. Also, ML has the ability to model complex relationships between variables and can help identify hidden structures. Another characteristic of the ML method is that it is used not only in EFA analysis, but also in confirmatory factor analysis (CFA), and this makes it used as a practical and optimal technique in different stages of research. One of the possible reasons for the low coefficients in the IF method is that the IF method is used in cases where the data are abnormal, we have outliers, the correlation between the items is weak and the commonality of the items is low. But as mentioned before, EFA assumptions were used in the present study, and this caused the communality coefficients in GLS and ML methods to be higher than the rest of the extraction methods. Finally, the choice between different extraction methods depends on the specific characteristics of the data, ... and research objectives. These results are similar to the findings of other studies, which show that the choice of extraction method has a great impact on EFA results (46,48,49,57-62,78,81-83).

In the present study, the highest percentage of variance explanation was related to the GLS method with 39.5%, followed by the ML method with 37.9%, and the lowest percentage of variance explanation was the IF method with 25.8%. The possible reason may be that GLS has been able to better identify the structure of the data effectively. In other words, GLS has a higher ability to model more complex relationships and correlations between variables (53,54,57,79,81,82,84,85). Also, the closeness of ML variance explanation percentage to GLS indicates the high efficiency of these two methods. However, under certain conditions such as normal distribution assumptions, the results may be slightly different, which of course can be neglected (55,58,59,61, 83,86). The possible reason that IF compared to the other two factors was less able to explain the available information, may be due to the presence of unrelated or weak variables, as well as the insensitivity of IF to the EFA assumptions (59,60,62,78,83,87).

The results showed that the communality and variance explanation percentage increased or decreased by changing the extraction methods, but changing the rotation type had no effect on their value. In fact, the rotation does not cause a change in the sum of the Eigenvalues, but by reducing the cross-loading, the factor loadings of the items are more appropriately distributed in each of the factors and make the Output more understandable (46,48,49,57,76). In other words, the main purpose of rotation is to simplify the structure of factor loadings to make their interpretation easier, so changing the type of rotation will not affect the variance explanation percentage. Choosing the type of rotation depends on the research topic, study concept, research objectives, data type, data characteristics, etc. (46,48,49,54,57,64,76,80).

In all extraction methods with any kind of rotation, the number of extracted factors was 8. It is obvious that with the same dataset, compliance with assumptions, similarity of study variables, etc., the number of extracted factors is similar. The more important thing is that there are several methods to determine the number of factors, including: eigenvalue higher than one, variance percentage higher than 5%, scree plot diagram, at least 3 items in each factor without cross-loading and logical arrangement of items according to theory and opinion Specialists (46,48,49,54,57,63, 64,71,76,80). Therefore, it is not possible to determine the number of extracted factors simply by the output table obtained from the analysis and observing the variance explanation percentage, but the number of factors should be determined according to the study concept and choosing the best extraction method and rotation type, as well as the better distribution of factor loadings. This finding is similar to many other studies that determined the number of factors based on different criteria (46,48,49,54,57,60, 61,63,71,77,78,80,81,83,85,87). In spite of the fact that in the present study, the coefficients of the GLS method were higher than other methods for the communality index and variance explanation percentage, but according to the mentioned criteria, ML was considered the best method.

At first glance, it may seem from the findings that the method with the highest communalities and the greatest percentage of explained variance should be selected in the final analysis. However, it is important to consider that the extraction method and type of rotation should not be determined solely based on the results of other articles or by examining output tables. A range of factors must be evaluated together, such as: the research topic, the concept of the study, research objectives, sample size, type of data, data quality, theory and hypotheses, the researcher's experience and knowledge in statistical analyses, comparison with other studies, interpretation of factors, eigenvalues greater than one, examination of EFA assumptions, correlations between items, KMO values, results of Bartlett's test, logical loading of items, distribution of items across each factor after rotation, criteria for determining the number of factors, minimum and maximum communalities, percentage of explained variance, number of extracted factors, cross-loadings, and the factor loadings for each item & etc.(4,43,45-49,52-55,57-63,65,71,76-87). In this study, despite GLS and then ML being the best extraction methods, an evaluation of these criteria along with the distribution of factor loadings for items in each factor indicated that the best arrangement of items in each factor corresponded to the ML method with Varimax rotation and four factors.

Limitations

The strength of this research that distinguishes it from other similar studies is its comprehensive examination of various extraction and rotation techniques in exploratory factor analysis for validating a questionnaire on children's addiction potential. No previous studies have simultaneously investigated such an in-depth approach regarding extraction methods and types of rotations, which represents an innovation in developing new tools and comparing different techniques in data analysis. This can assist researchers in selecting the best methods for data analysis. However, the study had limitations, especially regarding the research topic and the target group of the study. Such topics still have a social stigma, and researchers have faced difficulties and spent a lot of time obtaining the necessary permits and approvals.

In general, the results of this research indicate the appropriate validation of the questionnaire on children's addiction potential through exploratory factor analysis. In this study, the best extraction method was maximum likelihood, the best type of rotation was Varimax, and the optimal number of factors was determined to be four. Given the careful selection of extraction and rotation methods based on the characteristics of the data and the research objectives, this study can serve as a valid reference for researchers in the field of exploratory factor analysis and validation of measurement tools in the field of addiction. Also, the findings of this research can help to develop addiction prevention and treatment programs and lay the foundation for future research in this field. Accurate selection of extraction and rotation methods based on data characteristics and research objectives plays an important role in achieving valid results. Therefore, choosing the best method of extraction and rotation in EFA requires attention to several key factors, including: research objective, type of data, sample size, EFA assumptions, research topic, researcher's experience, evaluation of the criteria for determining the number of factors, etc. Paying attention to these factors can help researchers to obtain more accurate and reliable results from exploratory factor analysis.

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