Scale Formation: Scale Reliability Analysis and Exploratory Factor Analysis

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ABSTRACT

This chapter introduces two complementary statistical analysis techniques: **Scale Reliability Analysis** (which is used for establishing a single scale) and **Exploratory Factor Analysis** (which is used for establishing multiple scales). A **scale** is a group of fields of data which are believed to, or have been shown to, describe the same thing.

BACKGROUND

Rationale

Two major reasons for using scales are that it makes further analysis easier and reduces the risk of Type I errors. Collected data items, such as **Likert response values** (Trochim, 2021a) from a questionnaire, are often of **ordinal** data type whereas derived scales are **numerical** data. This means there are more and better analysis techniques which can be used with scales. Another reason for using scales is that they provide more reliable measures than individual items.

Creating Trial Items

When designing one or more scales for a psychological construct from scratch, it is advisable to start with a literature review or a focus group and not to limit the scope of the initial items included in the prospective scale(s) to the researcher's personal interpretation (Clark and Watson, 1995). This means it should be expected that the number of items in the scale(s) will be reduced down in the final (validated) version. Both Scale Reliability Analysis (SRA) and EFA facilitate this process. Alternatively, prospective items for new scales might be generated from several scales from different existing validated instruments.

Choice of Technique

If there are <u>10 or fewer initial items then it is recommended that SRA should be used</u>. If there are <u>more than about 25 initial items then it is recommended that EFA should be used</u>. If there are between about 10 and 25 initial items, it is recommended that the main technique of SRA, known as Principal Component Analysis (PCA), should first be used *once*, as this will give an initial indication as to whether more than one scale is present. The choice between these two techniques may also depend upon the context of the research and is mentioned briefly in the worked example in the next section (see also Trochim, 2021b). There are many false myths about SRA, including what is the most appropriate technique, the ideal number of items, and the minimum acceptable sample size. These will also be explored in the next section. EFA is a more complex process than SRA. It involves an initial assessment, a repeated analysis process, an overall validation process, and an individual scale validation process involving Scale Reliability Analysis. The main issue in validation is to check that the average inter-correlation of items on scales is significantly higher than the average intra-correlation between scales. If the overall validation process fails then an alternative form of EFA can be attempted. Both techniques are presented in the form of a theory introduction subsection followed by a case study. In addition, the issue of using SRA with small samples is discussed in the next section as a special case.

SCALE RELIABILITY ANALYSIS

Introduction

Scale Reliability Analysis (SRA) is a collection of techniques for establishing whether a group of items may be considered as a single construct which has a numerical value. There are several false myths in this subject. Firstly, the most commonly recommended statistic for this process is **Cronbach's Alpha** (1951). However, Field (2018) discourages the use of this technique, at least initially, as it may not identify the presence of multiple scales. Instead, he recommends beginning the process by using **Principal Component Analysis** (PCA, Pearson, 1901). The process of using PCA for SRA involves using a single component and checking its item loadings in the component matrix and the amount of total variance it explains. The specific decisions of what to do also depend upon the sample size and the size of the first eigenvalue. These are explained through the example in the case study with a sample size of about 100 and the advice for even smaller samples in the final subsection.

The secondly myth about SRA is the common statistical advice not to attempt a reliability analysis with a sample size less than 300 (e.g. see Kline, 1986). Student researchers often find it hard to obtain sample sizes this large. However, a simulation study by Yurdugül (2008) indicates that SRA with smaller samples is possible in certain circumstances. This is discussed in the final subsection. Thirdly, an often quoted rule of thumb with Cronbach's Alpha is a coefficient value above 0.7 is acceptable for psychological constructs (Kline, 1999). However, Cortina (1993) found that the size of a Cronbach's Alpha coefficient depends upon the number of items in the scale, with scales containing more items having higher coefficients.

This cut-off value myth is related to a fourth misconception that it is best to have as many items possible in a scale. This is clearly false as they would lead to a larger Cronbach's Alpha scores. Hinkin, Tracey and Enz (1997) recommend that initial (unvalidated) scales should contain <u>at least twice as many items</u> than those that are finally used and that final (validated) scales should be <u>four to six items long</u>. Thus, it is recommended that the <u>ideal number of items in an initial trial scale is around 10</u>. Provided that the final validated scale is not more than about 7 items, Kline's (1999) cut-off value can be used in a social science context. However, lower values may still be used with caution, e.g. Hair et al. (1998) recommend a cut-off value of 0.55. Finally, it is often assumed that the best way to calculate a scale's numerical value is simply to turn the values of the items into numbers and add them together. This is also not recommended. It is shown in the case study below that the weighting of retained items on a validated scale can vary between 0.4 and 1. Thus it would be appropriate if items more aligned to a scale should be given greater prominence in the construction of the scale value. The recommended technique for achieving this is the **regression model**.

Case Study

100 members of the public were asked nine questions about their perception of the professionalism of psychologists from which 99 usable responses were obtained. Each question used a traditional five point Likert response scale with 5 values ranging from *strongly disagree* to *strongly agree*. One of the items,

Violation_Likelihood, was reverse worded so the corresponding reversed variable *Violation_Likelihood_Reversed* was computed and included in the trial scale.NA PCA was run with a single component extraction. This led to the component matrix scores shown in Table 1.

Table 1: Component matrix scores for the extracted component

Name	Loading
Psychologists_Competence	0.767
Psychologists_Intergrity	0.831
Uphold_Prof_Standards	0.823
Respect_Rights	0.840
Welfare_Concern	0.769
Awareness_of_Prof_Responsibility	0.711
Positive_Consistency	0.711
Contribution_to_Research	0.718
Violation_Likelihood_Reversed	0.476
Psychologists_Competence	0.767

This single component accounted for 55.6% of the total variance with an eigenvalue of 5.006. According to Streiner (1994), as a general rule, the proportion of the total variance explained should be at least 50%. It is interesting to note that the lower loading of the *Violation_Likelihood_Reversed* item may indicate an issue with the validity of all the responses. It is common for respondents to give slightly positive values as then tend to try to please the questionnaire setter. Perhaps some of 99 respondents did not read the reverse worded question sufficiently closely and gave it a positive score. The following simulation studies were then cited:

- According to Guadagnoli and Velicer (1988), a component pattern is stable for a sample size of 100 provided that the component contains <u>at least four item loadings which are greater than 0.6</u>.
- They also recommend that items should not be removed from a scale provided that <u>their loadings are greater than 0.4</u>.
- According to Yurdugül (2008), the Cronbach's alpha coefficient is reliable for a sample size of 100 provided that the <u>first eigenvalue of the component matrix is greater than 3</u>.

Therefore, it was concluded that all 9 items should be retained and they constituted a single scale. As there is quite a large variation in the component scores it was decided to use the regression model to create the scale value rather than turning the individual items into numbers and adding them together. However, if the 9 items had not loaded sufficiently on the first component and the total variance explained by this component had been less than 50%, it would have been worth considering carrying out an EFA to determine whether two factors could be extracted. As mentioned above, this should be considered for a SRA with between about 10 and 25 initial items. A Cronbach's Alpha Reliability Analysis was then carried out with the same nine variables in order to verify the result. This returned a Cronbach's Alpha coefficient of 0.894. As there were nine items in this scale a slightly higher threshold should be taken for reliability than the normal cut-off value (0.7) as this applies to scales with the recommended number of items, i.e. between four and six items. However, as the Cronbach's Alpha coefficient was considerably higher than this threshold, it was concluded that the scale was also reliable according to this method.

Small Samples

According to Nunally and Bernstein (1994) there should always be less items in the scale than the sample size. Yurdugül (2008) analysed sample sizes of 30 and found that Cronbach's alpha coefficients were reliable provided the first eigenvalue of the PCA was greater than 6. Guadagnoli and Velicer (1988) analysed sample sizes of 50 and found that component patterns were stable provided the component loadings were at least 0.8. As they did not consider cases with less than four variables per component this rule should also be applied. The following summary is therefore advised:

- Reliability analysis should not be attempted for sample sizes less than 30.
- For sample sizes between 30 and 50, only Yurdugül's article should be cited but it is recommended that any items with a component loading less than 0.4 are removed from the scale and the PCA is re-run. If the resultant first eigenvalue is less than 6 then a reliability analysis should not be attempted. If less than four items have a component loading less than 0.8 then this should be discussed with the researcher making an informed decision about whether a reliability analysis should be attempted.
- For sample sizes between 50 and 100, both articles can be cited and both conditions should be satisfied. Again, after an initial PCA, any items with a component loading less than 0.4 should be removed from the scale and the analysis re-run. If the first eigenvalue is between 3 and 6 an informed decision should be made about a reliability analysis based on the sample size and the eigenvalue size by an interpretation of Table 1 based on a figure from Yurdugül's article (a scale is deemed to be reliable when the estimated relative bias mean is less than 0.01). If less than four items have a component loading greater than 0.8 then the advice in the point above should be followed.

Table 2: Relationship between Cronbach's Alpha bias and sample size. Adapted from (Yurdugül, 2008: 402).

First eigenvalue level	**Estimated relative bias mean for different sample sizes**			
	30	**100**	**300**	**500**
<3	0.082	0.019	0.007	0.003
Between 3 and 6	0.023	0.006	0.002	<0.001
>6	0.003	0.001	<0.001	<0.001

EXPLORATORY FACTOR ANALYSIS

Introduction

Exploratory Factor Analysis (EFA) is a process for identifying and validating groups of items in a questionnaire which represent the same thing, known as **scales**. The purpose of an EFA is to describe a multidimensional data set using fewer variables. Once a data collection instrument has been validated using EFA, another process called Confirmatory Factor Analysis can be used to confirm the factor analysis for additional data sets collected with the same instrument. However, this is beyond the scope of this chapter. There are two main forms of EFA known as Factor Analysis (FA) and Principal Component Analysis (PCA). The reduced dimensions produced by a FA are known as **factors** whereas those produced by a PCA are known as **components**. PCA will always work but FA may not converge to a solution. FA analyses the relationship between the individual item variances and common variances shared between items whereas the PCA analyses the relationships between the individual item variances and total (both common and error) variances shared between items. FA is therefore preferable to PCA in the early stages of an analysis as it enables the measurement of the ratio of an item's unique variance to its shared variance, known as its **communality**. As dimension reduction techniques seek to identify items with a shared variance, it is advisable to remove any item with a communality score less than 0.2 (Child, 2006). Items with low communality scores may indicate additional factors which could be explored in further studies by developing and measuring additional items (Costello and Osborne, 2005).

There are different **EFA methods**. When dealing with a single sample for further analysis (i.e. it is a population in terms of the EFA) **Principal Axis Factoring** is a commonly used method. Otherwise, when trying to develop and instrument to be used with other data sets in the future, it is advisable to use a sample-based EFA method such as **Maximum Likelihood** or **Kaiser's alpha factoring** (Field, 2018: 787). Whether to **rotate the factors** and the specific type of rotation used also needs to be decided. An **orthogonal rotation** can improve the solution from the unrotated one, but it forces the factors to be independent of each other (although this orthogonality refers to the loadings on all items in the questionnaire, rather than the items extracted in the final scales). The most popular orthogonal rotation technique is **varimax**.

The alternative to an orthogonal rotation is an **oblique rotation**. This allows a degree of correlation between the factors in order to improve the intercorrelation between the items within the factors. Although Reise et al. (2000) give several reasons why it should be considered, it is more difficult to interpret, so it advised that it should only be considered if the orthogonal solution is unacceptable. Field (2018: 794) recommends using either the **direct oblimin** or **promax** rotation with the default parameter settings. An oblique rotation creates two additional factor matrices called **pattern** and **structure**. It is <u>the pattern matrix which needs to be analysed</u> in the same way as the single rotated factor matrix obtained from orthogonal rotations. Each item is given a score for each factor. Following the advice of Field (2018: 805-806) <u>suppressing factor loadings less than 0.3</u> is recommended. Any item with all scores suppressed should be removed. Scores greater than 0.4 are considered stable (Guadagnoli and Velicer, 1988). Items should also not cross-load too highly between factors (measured by the ratio of loadings being greater than 3:4). The goal is to extract as many factors as possible with <u>at least 3 non-cross-loading items and with an acceptable loading score</u>. Items should be removed one by one until the solution satisfies all the requirements. The number of extracted factors may need to be reduced during the process.

After the EFA has been carried out there is a **validation process** that needs to be undertaken. There are different ways to extract and double-check the derived scales. For a successful analysis there should be <u>a higher average correlation between the items in the derived scales than the average correlation between</u>

the scales. The proportion of the total variance explained by the retained factors should be noted. As a general rule, this should be at least 50% (Streiner, 1994). The adequacy of the sample size should also be checked. The average communality should be checked for small samples. Finally, a test for multicollinearity based on the size of the determinant of the correlation matrix should be undertaken.

Step by step approach

1. Before starting an EFA, the values of the bivariate correlation matrix of all items should be analysed. High values indicate multicollinearity, although they are not a necessary condition (see Rockwell, 1975). Field (2018: 806) suggests items responsible for bivariate correlation scores greater than 0.9. If these occur only once between a pair of items there is no statistical means for deciding which item to remove – this should instead be based on a qualitative interpretation.
2. Start with an orthogonal rotation using varimax and run the analysis.
3. Remove any items with communalities less than 0.2 and re-run.
4. Optimize the number of factors – the number of factors given by Kaiser's criterion (eigenvalue greater than 1) often tends to be too high. The aim is to obtain as many factors as possible with at least 3 items with a loading greater than 0.4 and a low cross-loading. Reduce the number of factors to extract and re-run.
5. Remove any items with no factor loadings greater than 0.3 and re-run.
6. Remove any items with cross-loadings ratios greater than 3:4 starting with the one with the lowest absolute maximum loading on all the factors and re-run.
7. Once the solution has stabilized, check the average within and between factor correlations. To obtain the factors, use a PCA with the identified items and save the regression scores. If there is not an acceptable difference between the within and between factor average correlations, try an oblique rotation instead. It may be necessary to increase the number of iterations if the solution does not stabilize.
8. Provided the average within factor correlation is now significantly higher than the average between factor correlation, a number of final checks should be made:
    a. Check that the proportion of the total variance explained by the retained factors is at least 50% (Streiner, 1994).
    b. Check the adequacy of the sample size using the KMO statistic. A minimum acceptable score for this test is 0.5 (Kaiser, 1974).
    c. If the sample size is less than 300 check the average communality of the retained items. An average value above 0.6 is acceptable for samples less than 100, an average value between 0.5 and 0.6 is acceptable for sample sizes between 100 and 200 (MacCallum et al., 1999).
    d. The determinant of the correlation matrix should be greater than 0.00001 (Field, 2018: 799). A lower score might indicate that groups of three or more questions have high

intercorrelations, so the threshold for item removal should be reduced until this condition is satisfied.

e. The Cronbach's alpha coefficient for each scale can also be calculated.

9. If the goal of the analysis is to create scales of unique items then the meaning of the group of unique items which load on each factor should be interpreted to give each factor a meaningful name.

Case Study

171 business men and women responded to a questionnaire on entrepreneurship which was constructed from 8 groups of questions derived from existing questionnaires, comprising of a total of 39 questions. Each of the questions comprised of a five point Likert response scale. As the data from the questionnaire was to be used in a further analysis it was decided to carry out an Exploratory Factor Analysis using the Principal Axis Factoring technique and a varimax rotation. A Pearson bivariate correlation of all the items was undertaken. A conditional formatting was set for any correlations with an absolute value greater than 0.9. This returned a table of correlations including 10 unique pairs of correlations with an absolute value greater than 0.9, with the lowest absolute value being 0.922 (see Figure 1). As this was markedly higher than the threshold it was decided to remove one item from each of these pairs based on a qualitative analysis of the items, leaving 29 items. An EFA was then run on the remaining 29 items using a Principal Axis Factoring technique with a varimax rotation, providing the KMO statistic and determinant of the correlation matrix, retaining all factors with eigenvalues greater than 1 and suppressing all factor coefficients less than 0.3. The communalities of the initial solution were observed. All were larger than 0.2 so all the items were retained.

INSERT FIGURE 1 HERE

Figure 1: Bivariate correlation matrix with coefficients of absolute value above 0.9 highlighted

This led to an initial solution comprising of 8 factors. However the 7th and 8th factors did not have 3 items with loadings greater than 0.4 in the rotated factor matrix so they were excluded and the analysis re-run to extract 6 factors. Again, all the communalities were greater than 0.2. The rotated factor matrix for the analysis is shown in Table 2.

Table 2: Second rotated factor matrix with loadings of absolute value less than 0.3 suppressed and cross-loading items highlighted

	Factor					
Item	**1**	**2**	**3**	**4**	**5**	**6**
KST1				0.463		
KST2		0.606	0.413			
KST3	0.439	0.672				
KST4		0.442		-0.302		
KST5	0.305	0.648			0.390	
KSA1	0.601	0.331				
KSA2	0.384	0.328				

KSA3		0.659				
KSA4		0.465			0.377	
KSA5	0.427	0.304	0.325			
KSA6				0.429		
KSA7				0.660		
KSA8	0.688					
KL1			0.542			
KL2	0.432			0.485		
KL3	0.356			0.461		0.489
KL4	0.547					
KM1			0.486		0.364	
KM2	0.388		0.358		0.310	
KM3	0.493		0.452			
KM4	0.413		0.610			
KM5	0.649					
KM6	0.420		0.368			
KSB1			0.704			
KSB2						0.585
KSB3	0.450					0.659
KSB4					0.566	
KI1	0.381				0.623	
KI2	0.680				0.367	

However, many items in the rotated factor matrix (highlighted) cross loaded on more than one factor at a ratio higher than 3:4 or had a highest loading less than 0.4. These were removed in turn, starting with the item whose highest loading was the least (KSA2) and the analysis re-run. During the following analysis, in order that each factor had at least three items with loadings greater than 0.4, it was necessary to reduce the number of factors to 5. This eventually yielded a stable solution after 11 steps with 20 items – see Table 3.

Table 3: Stabilized rotated factor matrix with loadings of absolute value less than 0.3 suppressed and extracted items highlighted

	Factor				
Item	**1**	**2**	**3**	**4**	**5**
KST1					0.559
KST3	0.359	0.640			
KST4		0.556			-0.302
KST5		0.823			
KSA1	0.535	0.356			
KSA3		0.536			
KSA4		0.583			

KSA6					0.477
KSA7					0.573
KSA8	0.747				
KL1			0.613		
KL3				0.609	0.413
KL4	0.469			0.328	
KM1			0.522		
KM4	0.454		0.620		
KM5	0.666				
KSB1			0.661		
KSB2			0.355	0.523	
KSB3	0.382			0.719	
KI2	0.647	0.353			

Note: Even though KL3 had a loading greater than 0.4 on Factor 5 and KM4 had a loading greater than 0.4 on Factor 1 they were not included in the extracted factors because they had higher loadings on other factors. No other items were included in Factor 1 or Factor 5 with a lower absolute loading. It is only recommended that items are included more than once if it causes a factor to contain 3 items which would otherwise be removed.

Validation checks were run on this model:

- The average extracted communality was 0.501 which was just acceptable for this sample size (MacCallum et al., 1999). However, the communalities of the items in the fifth factor were all quite low which reduced the overall average value.
- The KMO statistic was 0.815, which is interpreted as "meritorious" by Kaiser and Rice (1974).
- The 5 extracted factors counted for 62.18% of the variation in the data, which is above the 50% threshold (Streiner, 1994).
- The correlation matrix determinant was 0.000364 which was well above the 0.00001 threshold (Field, 2018: 799).

A PCA was carried out on each identified factor with a single component extracted. The regression model of each factor was saved. A bivariate correlation was carried out between the factors. A Cronbach's Alpha Reliability Analysis was also undertaken. A summary of the extracted factors is shown in Table 4. The average between factor correlation was 0.320. This was considerably lower than the average within factor correlation of 0.417, so the factor extraction was deemed a success and an oblique rotation was not attempted. The extracted factors were then interpreted and the decisions of how to use them are also shown in Table 4.

Table 4: Summary of extracted factors

Factor	No. items	Average correlation	First eigenvalue	% of variance	Lowest absolute factor score	Cronbach's alpha	Decision

1	5	0.466	2.869	57.38	0.702	0.814	Stable
2	5	0.425	2.721	54.42	0.663	0.787	Stable
3	4	0.422	2.266	56.65	0.726	0.744	Stable
4	3	0.470	1.942	64.75	0.766	0.728	Acceptable
5	3	0.302	1.606	53.52	0.707	0.561	Use with caution
	Average	0.417					

CONCLUSION

This chapter has presented the complementary scale formation techniques of Scale Reliability Analysis and Exploratory Factor Analysis, which can both be used for establishing scales. There are many details to them which need to be followed for a successful extraction process. Several misconceptions about Scale Reliability Analysis have also been addressed. The main advantage of using these techniques is that they simplify further analysis.

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KEY TERMS AND DEFINITIONS

Communality: The ratio of an individual item's unique variance to its shared variance.

Component: A type of scale which has been derived from a PCA.

Cronbach's Alpha Reliability Analysis: A technique for Scale Reliability Analysis.

Exploratory Factor Analysis (EFA): A collection of techniques for establishing whether a group of items may be considered as several scales which have numerical values.

Factor: A type of scale which has been derived from Factor Analysis.

Factor Analysis: A subset of EFA techniques which compares item variance against shared variance.

Item: A single field of collected data, such as data derived from a single question in a questionnaire.

Likert response values: A collection of ordinal values for a single answer multiple choice question on a questionnaire. A common example is the five values: strongly disagree, disagree, neutral, agree and strongly agree.

Ordinal data: A type of categorical data where the values have a natural ordering, such as Likert response values

Principal Component Analysis (PCA): A technique for both EFA and Scale Reliability Analysis which compares item variance against total variance.

Scale: A group of fields of data which are believed to, or have been shown to, describe the same thing, such as a psychological construct.

Scale Reliability Analysis (SRA): A collection of techniques for establishing whether a group of items may be considered as a single construct which has a numerical value.