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Principal Component and Factor Analysis

Learning Objectives

After reading this chapter, you should understand:
- The basics of principal component and factor analysis.
- The principles of exploratory and confirmatory factor analysis.
- Key terms, such as communality, eigenvalues, factor loadings, and factor scores.
- What factor rotation is.
- How to determine whether data are suitable for carrying out an exploratory factor analysis.
- How to interpret SPSS principal component analysis output.
- The principles of reliability analysis and its execution in SPSS.
- The concept of structural equation modeling.

Keywords

Anti-image · Bartlett method · Bartlett's test of sphericity · Communality · Components · Confirmatory factor analysis · Correlation residuals · Covariance-based structural equation modeling · Cronbach's Alpha · Direct oblimin rotation · Eigenvalue · Eigenvectors · Exploratory factor analysis · Factor analysis · Factor loading · Factor rotation · Factor scores · Factor weights · Factors · Internal consistency reliability · Kaiser criterion · Kaiser–Meyer–Olkin criterion · Latent root criterion · Measure of sampling adequacy · Oblique rotation · Orthogonal rotation · Parallel analysis · Partial least squares structural equation modeling · Path diagram · Principal axis factoring · Principal component analysis · Principal components · Principal factor analysis · Promax rotation · Quartimax rotation · Regression method · Reliability analysis · Scree plot · Split-half reliability · Structural equation modeling · Test-retest reliability · Varimax rotation

8.1 Introduction

Principal component analysis (**PCA**) and **factor analysis** (also called **principal factor analysis** or **principal axis factoring**) are two methods for identifying structure within a set of variables. Many analyses involve large numbers of variables that are difficult to interpret. Using PCA or factor analysis helps find interrelationships between variables (usually called items) to identify a smaller number of unifying variables called **factors**. Consider the example of a soccer club whose management wants to measure the satisfaction of the fans. The management could, for instance, measure fan satisfaction by asking how satisfied the fans are with the (1) assortment of merchandise, (2) quality of merchandise, and (3) prices of merchandise. It is likely that these three items together measure satisfaction with the merchandise. Through the application of PCA or factor analysis, we can determine whether a single factor represents the three satisfaction items well. Practically, PCA and factor analysis are applied to understand much larger sets of variables, tens or even hundreds, when just reading the variables' descriptions does not determine an obvious or immediate number of factors.

PCA and factor analysis both explain patterns of correlations within a set of observed variables. That is, they identify sets of highly correlated variables and infer an underlying factor structure. While PCA and factor analysis are very similar in the way they arrive at a solution, they differ fundamentally in their assumptions of the variables' nature and their treatment in the analysis. Due to these differences, the methods follow different research objectives, which dictate their areas of application. While the PCA's objective is to *reproduce*

a data structure, as well as possible only using a few factors, factor analysis aims to *explain* the variables' correlations using factors (e.g., Hair et al. 2010; Matsunaga 2010; Mulaik 2009).[1] We will discuss these differences and their implications in this chapter.

Both PCA and factor analysis can be used for exploratory or confirmatory purposes. What are exploratory and confirmatory factor analyses? Comparing the left and right panels of ◘ Fig 8.1 shows us the difference. **Exploratory factor analysis**, often simply referred to as EFA, does not rely on previous ideas on the factor structure we may find. That is, there may be relationships (indicated by the arrows) between each factor (indicated by ovals) and each item. While some of these relationships may be weak (indicated by the dotted arrows), others are more pronounced, suggesting that these items represent an underlying factor well. The left panel of ◘ Fig. 8.1 illustrates this point. Thus, an exploratory factor analysis reveals the number of factors and the items belonging to a specific factor. In a **confirmatory factor analysis**, usually simply referred to as CFA, there may only be relationships between a factor and specific items. In the right panel of ◘ Fig. 8.1, the first three items relate to factor 1, whereas the last two items relate to factor 2. Different from the exploratory factor analysis, in a confirmatory factor analysis, we have clear expectations of the factor structure (e.g., because researchers have proposed a scale that we want to adapt for our study) and we want to test for the expected structure.

In this chapter, we primarily deal with exploratory factor analysis, as it conveys the principles that underlie all factor analytic procedures and because the two techniques are (almost) identical from a statistical point of view. Nevertheless, we will also discuss an important aspect of confirmatory factor analysis, namely **reliability analysis**, which tests the consistency of a measurement scale (see ▶ Chap. 3). We will also briefly introduce a specific confirmatory factor analysis approach called **structural equation modeling** (often simply referred to as SEM). Structural equation modeling differs statistically and practically from PCA and factor analysis. It is not only used to evaluate how well observed variables relate to factors but also to analyze hypothesized relationships between factors that the researcher specifies prior to the analysis based on theory and logic.
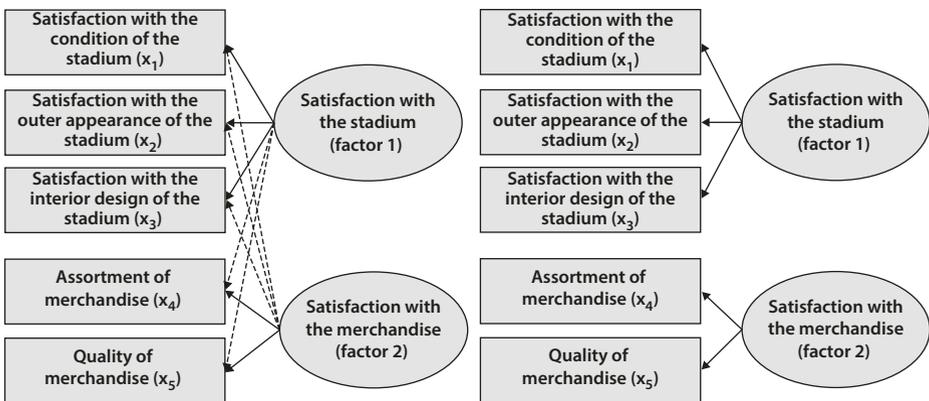

◘ **Fig. 8.1**   Exploratory factor analysis (left) and confirmatory factor analysis (right)

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1   Other methods for carrying out factor analyses include, for example, unweighted least squares, generalized least squares, or maximum likelihood but these are statistically complex.

8.2 Understanding Principal Component and Factor Analysis

8.2.1 Why Use Principal Component and Factor Analysis?

Researchers often face the problem of large questionnaires comprising many *items*. For example, in a survey of a major German soccer club, the management was particularly interested in identifying and evaluating performance features that relate to soccer fans' satisfaction (Sarstedt et al. 2014). Examples of relevant features include the stadium, the team composition and their success, the trainer, and the management. The club therefore commissioned a questionnaire comprising 99 previously identified items by means of literature databases and focus groups of fans. All the items were measured on scales ranging from 1 ("very dissatisfied") to 7 ("very satisfied"). ◘ Table 8.1 shows an overview of some items considered in the study.

◘ **Table 8.1** Items in the soccer fan satisfaction study

| **Satisfaction with …**	
Condition of the stadium	Public appearances of the players
Interior design of the stadium	Number of stars in the team
Outer appearance of the stadium	Interaction of players with fans
Signposting outside the stadium	Volume of the loudspeakers in the stadium
Signposting inside the stadium	Choice of music in the stadium
Roofing inside the stadium	Entertainment program in the stadium
Comfort of the seats	Stadium speaker
Video score boards in the stadium	Newsmagazine of the stadium
Condition of the restrooms	Price of annual season ticket
Tidiness within the stadium	Entry fees
Size of the stadium	Offers of reduced tickets
View onto the playing field	Design of the home jersey
Number of restrooms	Design of the away jersey
Sponsors' advertisements in the stadium	Assortment of merchandise
Location of the stadium	Quality of merchandise
Name of the stadium	Prices of merchandise
Determination and commitment of the players	Pre-sale of tickets
Current success regarding matches	Online-shop
Identification of the players with the club	Opening times of the fan-shops
Quality of the team composition	Accessibility of the fan-shops
Presence of a player with whom fans can identify	Behavior of the sales persons in the fan shops

As you can imagine, tackling such a large set of items is problematic, because it provides quite complex data. Given the task of identifying and evaluating performance features that relate to soccer fans' satisfaction (measured by "Overall, how satisfied are you with your soccer club"), we cannot simply compare the items on a pairwise basis. It is far more reasonable to consider the factor structure first. For example, satisfaction with the condition of the stadium (x_1), outer appearance of the stadium (x_2), and interior design of the stadium (x_3) cover similar aspects that relate to the respondents' satisfaction with the stadium. If a soccer fan is generally very satisfied with the stadium, he/she will most likely answer all three items positively. Conversely, if a respondent is generally dissatisfied with the stadium, he/she is most likely to be rather dissatisfied with all the performance aspects of the stadium, such as the outer appearance and interior design. Consequently, these three items are likely to be highly correlated—they cover related aspects of the respondents' overall satisfaction with the stadium. More precisely, these items can be interpreted as manifestations of the factor capturing the "joint meaning" of the items related to it. The arrows pointing from the factor to the items in ◘ Fig. 8.1 indicate this point. In our example, the "joint meaning" of the three items could be described as *satisfaction with the stadium*, since the items represent somewhat different, yet related, aspects of the stadium. Likewise, there is a second factor that relates to the two items x_4 and x_5, which, like the first factor, shares a common meaning, namely *satisfaction with the merchandise*.
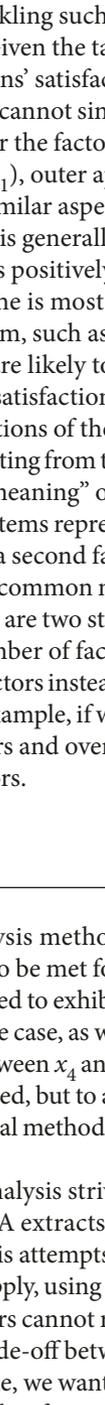
PCA and factor analysis are two statistical procedures that draw on item correlations in order to find a small number of factors. Having conducted the analysis, we can make use of few (uncorrelated) factors instead of many variables, thus significantly reducing the analysis's complexity. For example, if we find six factors, we only need to consider six correlations between the factors and overall satisfaction, which means that the recommendations will rely on six factors.

8.2.2 Analysis Steps

Like any multivariate analysis method, PCA and factor analysis are subject to certain requirements, which need to be met for the analysis to be meaningful. A crucial requirement is that the variables need to exhibit a certain degree of correlation. In our example in ◘ Fig. 8.1, this is probably the case, as we expect increased correlations between x_1, x_2, and x_3, on the one hand, and between x_4 and x_5 on the other. Other items, such as x_1 and x_4, are probably somewhat correlated, but to a lesser degree than the group of items x_1, x_2, and x_3 and the pair x_4 and x_5. Several methods allow for testing whether the item correlations are sufficiently high.
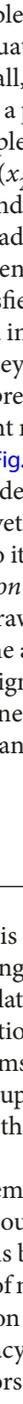
Both PCA and factor analysis strive to reduce the overall item set to a smaller set of factors. More precisely, PCA extracts factors such that they account for variables' variance, whereas factor analysis attempts to explain the correlations between the variables. Whichever approach you apply, using only a few factors instead of many items reduces its precision, because the factors cannot represent all the information included in the items. Consequently, there is a trade-off between simplicity and accuracy. In order to make the analysis as simple as possible, we want to extract only a few factors. At the same time, we do not want to lose too much information by having too few factors. This trade-off has to be addressed in any PCA and factor analysis when deciding how many factors to extract from the data.
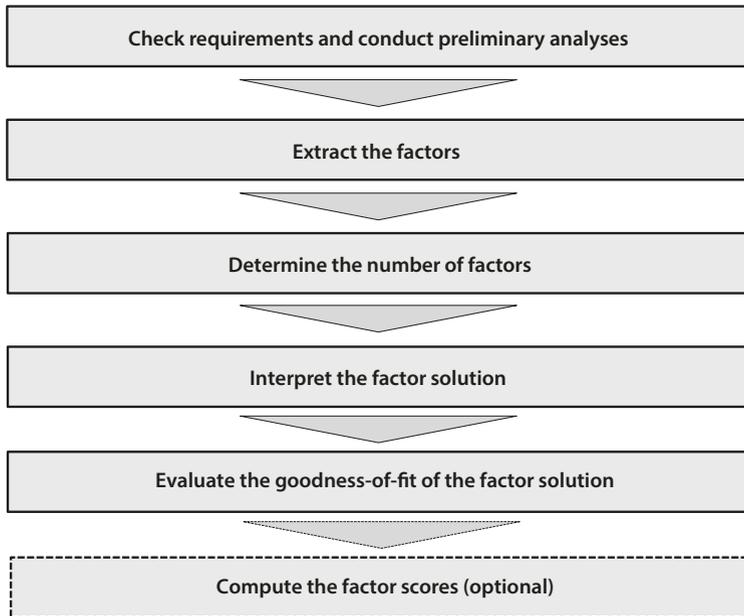
Fig. 8.2 Steps involved in a PCA

Once the number of factors to retain from the data has been identified, we can proceed with the interpretation of the factor solution. This step requires us to produce a label for each factor that best characterizes the joint meaning of all the variables associated with it. This step is often challenging, but there are ways of facilitating the interpretation of the factor solution. Finally, we have to assess how well the factors reproduce the data. This is done by examining the solution's goodness-of-fit, which completes the standard analysis. However, if we wish to continue using the results in further analyses, we need to calculate the factor scores. Factor scores are linear combinations of the items and can be used as variables in follow-up analyses.

■ Figure 8.2 illustrates the steps involved in the analysis; we will discuss these in more detail in the following sections. In doing so, our theoretical descriptions and illustrations will focus on the PCA, as this method is easier to grasp. However, most of our descriptions also apply to factor analysis.

8.3 Principal Component Analysis

8.3.1 Check Requirements and Conduct Preliminary Analyses

Before carrying out a PCA, we have to consider several requirements, which we can test by answering the following questions:
– Are the measurement scales appropriate?
– Is the sample size sufficiently large?
– Are the observations independent?
– Are the variables sufficiently correlated?

■ **Are the measurement scales appropriate?**

For a PCA, it is best to have data measured on an interval or ratio scale. In practical applications, items measured on an ordinal scale level have become common. Ordinal scales can be used if:

━ the scale points are equidistant, which means that the difference in the wording between scale steps is the same (see ► Chap. 3), *and*
━ there are five or more response categories.

■ **Is the sample size sufficiently large?**

Another point of concern is the sample size. As a rule of thumb, the number of (valid) observations should be at least ten times the number of items used for analysis. This only provides a rough indication of the necessary sample size. Fortunately, researchers have conducted studies to determine minimum sample size requirements, which depend on other aspects of the study. MacCallum et al. (1999) suggest the following:

━ When all communalities (we will discuss this term in ► Sect. 8.3.2.4) are above 0.60, small sample sizes of below 100 are adequate.
━ With communalities around 0.50, sample sizes between 100 and 200 are sufficient.
━ When communalities are consistently low, with many or all under 0.50, a sample size between 100 and 200 is adequate if the number of factors is small and each of these is measured with six or more items.
━ When communalities are consistently low and the factors numbers are high or are measured with only few items (i.e., 3 or less), 300 observations are recommended.

■ **Are the observations independent?**

We have to ensure that the observations are independent. This means that the observations need to be completely unrelated (see ► Chap. 3). If we use dependent observations, we would introduce "artificial" correlations, which are not due to an underlying factor structure, but simply to the same respondents having answered the same questions multiple times.

■ **Are the variables sufficiently correlated?**

As indicated before, PCA is based on correlations between items. Consequently, conducting a PCA only makes sense if the items correlate sufficiently. The problem is deciding what "sufficient" actually means.

An obvious step is to examine the correlation matrix (► Chap. 5). Naturally, we want the correlations between different items to be as high as possible, but they will not always be. In our previous example, we expect high correlations between x_1, x_2, and x_3, on the one hand, and x_4 and x_5 on the other. Conversely, we might expect lower correlations between, for example, x_1 and x_4 and between x_3 and x_5. Thus, not all of the correlation matrix's elements need to have high values. The PCA depends on the *relative* size of the correlations. Therefore, if single correlations are very low, this is not necessarily problematic! Only when all the correlations are around zero, PCA is no longer useful. In addition, the statistical significance of each correlation coefficient helps decide whether it differs significantly from zero.

There are additional measures to determine whether the items correlate sufficiently. One is the **anti-image**. The anti-image describes the portion of an item's variance that is independent of another item in the analysis. Obviously, we want all items to be highly correlated, so that the anti-images of an item set are as small as possible. Initially, we do

◨ **Table 8.2** Threshold values for KMO and MSA

KMO/MSA value	Adequacy of the correlations
Below 0.50	Unacceptable
0.50–0.59	Miserable
0.60–0.69	Mediocre
0.70–0.79	Middling
0.80–0.89	Meritorious
0.90 and higher	Marvelous

not interpret the anti-image values directly, but use a measure based on the anti-image concept: **The Kaiser–Meyer–Olkin** (**KMO**) criterion. The KMO criterion, also called the **measure of sampling adequacy** (**MSA**), indicates whether the other variables in the dataset can explain the correlations between variables. Kaiser (1974), who introduced the statistic, recommends a set of nicely labeled threshold values for KMO and MSA, which ◨ Table 8.2 presents.

The **Bartlett's test of sphericity** can be used to test the null hypothesis that the correlation matrix is a diagonal matrix (i.e., all non-diagonal elements are zero) in the population. Since we need high correlations for PCA, we want to reject the null hypothesis. A large test statistic value and corresponding a small p-value will favor the rejection of the hypothesis. In practical applications, it is virtually impossible not to reject this null hypothesis, as typically there are some correlations, particularly in larger sets of items. In addition, PCA is typically used with large samples, a situation, which favors the rejection of the null hypothesis. Thus, Bartlett's test is of rather limited value for assessing whether the variables are sufficiently correlated.

To summarize, the correlation matrix with the associated significance levels provides a first insight into the correlation structures. However, the final decision of whether the data are appropriate for PCA should be primarily based on the KMO statistic. If this measure indicates sufficiently correlated variables, we can continue the analysis of the results. If not, we should try to identify items that correlate only weakly with the remaining items and remove them. In Box 8.1, we discuss how to do this.

Box 8.1 Identifying problematic items

Examining the correlation matrix and the significance levels of correlations allows identifying items that correlate only weakly with the remaining items. An even better approach is examining the variable-specific MSA values, which are interpreted like the overall KMO statistic (see ◨ Table 8.2). In fact, the KMO statistic is simply the overall mean of all variable-specific MSA values. Consequently, all the MSA values should also lie above the threshold level of 0.50. If this is not the case, consider removing this item from the analysis. An item's communality (see ▶ Sect. 8.3.2.4) can also serve as a useful indicator of how well the factors extracted represent an item. However, communalities are mostly considered when evaluating the solution's goodness-of-fit.

8.3.2 **Extract the Factors**

8.3.2.1 **Principal Component Analysis vs. Factor Analysis**

Factor analysis assumes that each variable's variance can be divided into common variance (i.e., variance shared with all the other variables in the analysis) and unique variance (◘ Fig. 8.3), the latter of which can be further broken down into specific variance (i.e., variance associated with only one specific variable) and error variance (i.e., variance due to measurement error). The method, however, can only reproduce common variance. Thereby factor analysis explicitly recognizes the presence of error. Conversely, PCA assumes that all variance is common variance, which factor extraction can fully explain (e.g., Preacher and MacCallum 2003). These differences entail different interpretations of the analysis's outcomes. PCA asks:

» Which umbrella term can we use to summarize a set of variables that loads highly on a specific factor?

Conversely, factor analysis asks:

» What is the common reason for the strong correlations between a set of variables?

From a theoretical perspective, the assumption that there is a unique variance for which the factors cannot fully account, is generally more realistic, but simultaneously more restrictive. Although theoretically sound, this restriction can sometimes lead to complications in the analysis, which have contributed to the widespread use of PCA, especially in market research practice.

Researchers usually suggest using PCA when data reduction is the primary concern; that is, when the focus is to extract a minimum number of factors that account for a maximum proportion of the variables' total variance. In contrast, if the primary concern is to identify latent dimensions represented in the variables, factor analysis should be applied. However, prior research has shown that both approaches arrive at essentially the same result when
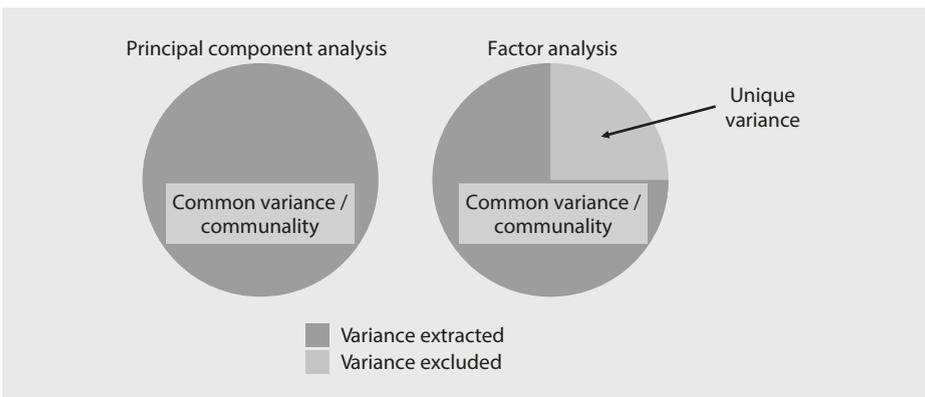
◘ **Fig. 8.3**   Principal component analysis vs. factor analysis

- more than 30 variables are used, *or*
- most of the variables' communalities exceed 0.60.

With 20 or fewer variables and communalities below 0.40—which are clearly undesirable in empirical research—the differences are probably pronounced (Stevens 2009).

Apart from these conceptual differences in the variables' nature, PCA and factor analysis differ in the aim of their analysis. Whereas the goal of factor analysis is to explain the correlations between the variables, PCA focuses on explaining the variables' variances. That is, the PCA's objective is to determine the linear combinations of the variables that retain as much information from the original variables as possible. Strictly speaking, PCA does not extract factors, but *components*, which are labeled as such in SPSS.

Despite these differences, which have very little relevance in many common research settings in practice, PCA and factor analysis have many points in common. For example, the methods follow very similar ways to arrive at a solution and their interpretations of statistical measures, such as KMO, eigenvalues, or factor loadings, are (almost) identical. In fact, SPSS blends these two procedures when running a PCA as the program initially applies a factor analysis but rescales the estimates such that they conform to a PCA. That way, the analysis assumes that the entire variance is common but produces (rotated) loadings (we will discuss factor rotation in ► Sect. 8.3.4.1), which facilitate the interpretation of the factors.

Despite the small differences of PCA and factor analysis in most research settings, researchers have strong feelings about the choice of PCA or factor analysis. Cliff (1987, p. 349) summarizes this issue well, by noting that proponents of factor analysis "insist that components analysis is at best a common factor analysis with some error added and at worst an unrecognizable hodgepodge of things from which nothing can be determined." For further discussions on this topic, see also Velicer and Jackson (1990) and Widaman (1993).[2]

8.3.2.2 How Does Factor Extraction Work?

When extracting factors, PCA's objective is to reproduce a data structure with only a few factors. PCA does this by generating a new set of factors as linear composites of the original variables, which reproduces the original variables' variance as best as possible. These linear composites are called **principal components**, but, for simplicity's sake, we refer to them as factors. More precisely, PCA computes **eigenvectors**. These eigenvectors include so called **factor weights**, which extract the maximum possible variance of all the variables, with successive factoring continuing until a significant share of the variance is explained.

Operationally, the first factor is extracted in such a way that it maximizes the variance accounted for in the variables. We can visualize this easily by examining the vector space illustrated in ◻ Fig. 8.4. In this example, we have five variables (x_1–x_5) represented

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2   Related discussions have been raised in structural equation modeling, where researchers have heatedly discussed the strengths and limitations of factor-based and component-based approaches (e.g. Sarstedt et al. 2016a; Hair et al. 2017b).

◻ Fig. 8.4   Factor extraction[3]
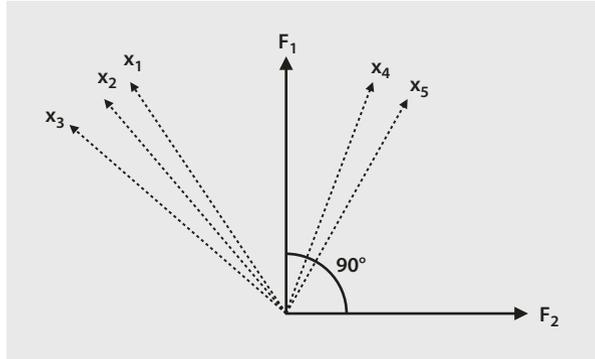
by five vectors starting at the zero point, with each vector's length standardized to one. To maximize the variance accounted for, the first factor F_1 is fitted into this vector space in such a way that the sum of all the angles between this factor and the five variables in the vector space is minimized. We do this to interpret the angle between two vectors as correlations. For example, if the factor's vector and a variable's vector are congruent, the angle between these two is zero, indicating that the factor and the variable correlate perfectly. On the other hand, if the factor and the variable are uncorrelated, the angle between these two is 90°. This correlation between a (unit-scaled) factor and a variable is called the **factor loading**. Note that factor weights and factor loadings essentially express the same thing—the relationships between variables and factors—but they are based on different scales.

After extracting F_1, a second factor (F_2) is extracted, which maximizes the remaining variance accounted for. The second factor is fitted at a 90° angle into the vector space (◻ Fig. 8.4) and is therefore uncorrelated with the first factor.[4] If we extract a third factor, it will explain the maximum amount of variance for which factors 1 and 2 have hitherto not accounted. This factor will also be fitted at a 90° angle to the first two factors, making it independent from the first two factors (we don't illustrate this third factor in ◻ Fig. 8.4, as this is a three-dimensional space). The fact that the factors are uncorrelated is an important feature, as we can use them to replace many highly correlated variables in follow-up analyses. For example, using uncorrelated factors as independent variables in a regression analysis helps solve potential *collinearity* issues (▶ Chap. 7).

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3   Note that ◻ Fig. 8.3 describes a special case, as the five variables are scaled down into a two-dimensional space. In this set-up, it would be possible for the two factors to explain all five items. However, in real-life, the five items span a five-dimensional vector space.

4   Note that this changes when oblique rotation is used. We will discuss factor rotation later in this chapter.

The Explained Visually webpage offers an excellent illustration of two- and three-dimensional factor extraction.


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http://setosa.io/ev/principal-component-analysis/

An important PCA feature is that it works with standardized variables (see ▶ Chap. 5 for an explanation of what standardized variables are). Standardizing variables has important implications for our analysis in two respects. First, we can assess each factor's eigenvalue, which indicates how much a specific factor extracts all of the variables' variance (see ▶ Sect. 8.3.2.3). Second, the standardization of variables allows for assessing each variable's communality, which describes how much the factors extracted capture or reproduce each variable's variance (see ▶ Sect. 8.3.2.4).

8.3.2.3 What Are Eigenvalues?

To understand the concept of **eigenvalues**, think of the soccer fan satisfaction study (◨ Fig. 8.1). In this example, there are five variables. As all the variables are standardized prior to the analysis, each has a variance of 1. In a simplified way, we could say that the overall information (i.e., variance) that we want to reproduce through factor extraction is 5 units. Let's assume that we extract the two factors presented above.

The first factor's eigenvalue indicates how much of the total variance the factor accounts for. Each variable has a variance of 1, which means the number of variables is the total variance (i.e., 5 variables = 5 units of variance). If a factor has an eigenvalue of, let's say 2.10, it covers the information of 2.10 variables or, put differently, accounts for 2.10/5.00 = 42 % of the overall variance (◨ Fig. 8.5).

Extracting a second factor will allow us to explain another part of the remaining variance (i.e., 5.00 − 2.10 = 2.90 units, ◨ Fig. 8.5). However, the eigenvalue of the second factor will always be smaller than that of the first factor. Assume that the second factor has an eigenvalue of 1.30 units. The second factor then accounts for 1.30/5.00 = 26 % of the overall variance. Together, these two factors explain (2.10 + 1.30)/5.00 = 68 % of the
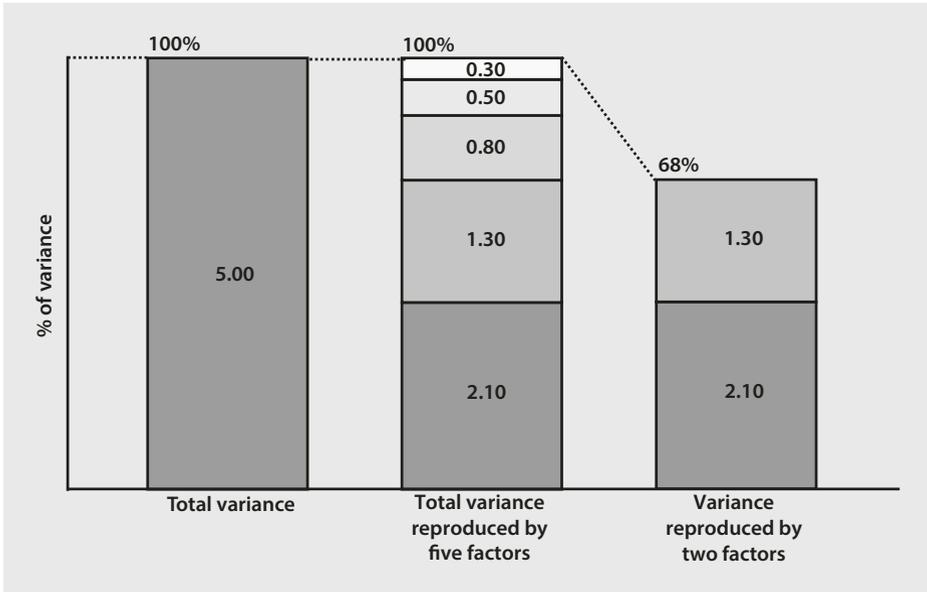
☐ Fig. 8.5   Total variance explained by variables and factors

overall variance. Every additional factor extracted increases the variance accounted for until we have extracted as many factors as there are variables. In this case, the factors account for 100 % of the overall variance, which means that the factors reproduce the complete variance.

For readers interested in the statistical principles, the Explained Visually webpage illustrates the concepts of eigenvalues and eigenvectors.

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http://setosa.io/ev/eigenvectors-and-eigenvalues/

Following the PCA approach, we assume that factor extraction can reproduce each variable's entire variance. In other words, we assume that each variable's variance is common; that is, the variance is shared with other variables. This differs in factor analysis, in which each variable can also have a unique variance.

8.3.2.4 What Is Communality?

Whereas the eigenvalue tells us how much variance each factor accounts for, the **communality** indicates how much variance of each variable factor extraction can reproduce. There is no commonly agreed threshold for a variable's communality, as this depends strongly on the complexity of the analysis at hand. However, generally, the extracted factors should account for at least 50 % of a variable's variance. Thus, the communalities should be above 0.50. Every additional factor extracted will increase the explained variance, and if we extract as many factors as there are variables (in our example five), each variable's communality would be 1.00. The factors extracted would then fully explain each variable; that is, the first factor will explain a certain amount of each variable's variance, the second factor another part, and so on.

However, since our overall objective is to reduce the number of variables through factor extraction, we should extract only a few factors that account for a high degree of overall variance. This raises the question of how to decide on the number of factors to extract from the data, which we discuss in the following section.

8.3.3 Determine the Number of Factors

Determining the number of factors to extract from the data is a crucial and challenging step in any PCA. Several approaches offer guidance in this respect, but most researchers do not pick just one method, but use multiple ones. If different methods suggest the same number of factors, this leads to greater confidence in the results.

8.3.3.1 The Kaiser Criterion

An intuitive way to decide on the number of factors is to extract all the factors with an eigenvalue greater than 1. The reason for this is that each factor with an eigenvalue greater than 1 accounts for more variance than a single variable (remember, we are looking at standardized variables, which is why each variable's variance is exactly 1). As the objective of PCA is to reduce the overall number of variables, each factor should of course account for more variance than a single variable can. If this occurs, then this factor is useful for reducing the set of variables. Extracting all the factors with an eigenvalue greater than 1 is frequently called the **Kaiser criterion** or **latent root criterion** and is commonly used to determine the number of factors. However, the Kaiser criterion is well known for over-specifying the number of factors; that is, the criterion suggests more factors than it should (e.g., Russell 2002; Zwick and Velicer 1986).

8.3.3.2 The Scree Plot

Another popular way to decide on the number of factors to extract is to plot each factor's eigenvalue (*y*-axis) against the factor with which it is associated (*x*-axis). This results in a **scree plot**, which typically has a distinct break in it, thereby showing the "correct"

number of factors (Cattell 1966). This distinct break is called the "*elbow*." Researchers typically recommend retaining all factors *above* this break, as they contribute most to the explanation of the variance in the dataset. Thus, we select one factor less than indicated by the elbow.

8.3.3.3 Parallel Analysis

A large body of review papers and simulation studies has produced a prescriptive consensus that Horn's (1965) **parallel analysis** is the best method for deciding how many factors to extract (e.g., Dinno 2009; Hayton et al. 2004; Henson and Roberts 2006; Matsunga 2010; Zwick and Velicer 1986). The rationale underlying parallel analysis is that factors from real data with a valid underlying factor structure should have larger eigenvalues than those derived from randomly generated data (actually pseudorandom deviates) with the same sample size and number of variables. Parallel analysis involves several steps. First, a large number of datasets are randomly generated that have the same number of observations and variables as the original dataset. Parallel PCAs are then run on each of the datasets (hence, parallel analysis), resulting in many slightly different sets of randomly generated eigenvalues. We then compare the randomly generated eigenvalues with those from the original analysis. Only factors whose original eigenvalues are larger than the 95th percentile of the eigenvalues should be retained (Longman et al. 1989).

8.3.3.4 Expectations

When, for example, replicating a previous market research study, we might have a priori information on the number of factors we want to find. For example, if a previous study suggests that a certain item set comprises five factors, we should extract the same number of factors, even if statistical criteria, such as the scree plot, suggest a different number. Similarly, theory might suggest that a certain number of factors should be extracted from the data.

Strictly speaking, these are confirmatory approaches to PCA, which blur the distinction between these two factor analysis types. Ultimately however, we should not only rely on the data, but keep in mind that the research results should be interpretable and actionable for market research practice. Once we have decided on the number of factors to retain from the data, we can start interpreting the factor solution.

> **Whatever combination of approaches we use to determine the number of factors, the factors extracted should account for at least 50 % of the total variance explained (75 % or more is recommended).**

8.3.4 Interpret the Factor Solution

8.3.4.1 Rotate the Factors

To interpret the solution, we have to determine which variables relate to each of the factors extracted. We do this by examining the *factor loadings*, which represent the correlations between the factors and the variables and can take values ranging from −1 to +1. A high

factor loading indicates that a certain factor represents a variable well. Subsequently, we look for high *absolute* values, because the correlation between a variable and a factor can also be negative. Using the highest absolute factor loadings, we "assign" each variable to a certain factor and then produce a label for each factor that best characterizes the joint meaning of all the variables associated with it. This labeling is subjective, but a key PCA step. An example of a label is the respondents' satisfaction with the stadium, which represents the items referring to its condition, outer appearance, and interior design (◘ Fig. 8.1).

We can make use of **factor rotation** to facilitate the factors' interpretation. We do not have to rotate the factor solution, but it will facilitate interpreting the findings, particularly if we have a reasonably large number of items (say six or more). To understand what factor rotation is all about, once again consider the factor structure described in ◘ Fig. 8.4. Here, we see that both factors relate to the variables in the set. However, the first factor appears to generally correlate more strongly with the variables, whereas the second factor only correlates weakly with the variables (to clarify, we look for small angles between the factors and variables). This implies that we "assign" all variables to the first factor without taking the second into consideration. This does not appear to be very meaningful, as we want both factors to represent certain facets of the variable set. Factor rotation can resolve this problem. By rotating the factor axes, we can create a situation in which a set of variables loads highly on only one specific factor, whereas another set loads highly on another. ◘ Figure 8.6 illustrates the factor rotation graphically.

On the left side of the figure, we see that both factors are orthogonally rotated 49°, meaning that a 90° angle is maintained between the factors during the rotation procedure. Consequently, the factors remain uncorrelated, which is in line with the PCA's initial objective. By rotating the first factor from F_1 to F_1', it is now strongly related to variables x_1, x_2, and x_3, but weakly related to x_4 and x_5. Conversely, by rotating the second factor from F_2 to F_2', it is now strongly related to x_4 and x_5, but weakly related to the remaining variables. The assignment of the variables is now much clearer, which facilitates the interpretation of the factors significantly.

Various **orthogonal rotation** methods exist, all of which differ with regard to their treatment of the loading structure. The **varimax rotation** is the best-known and this procedure
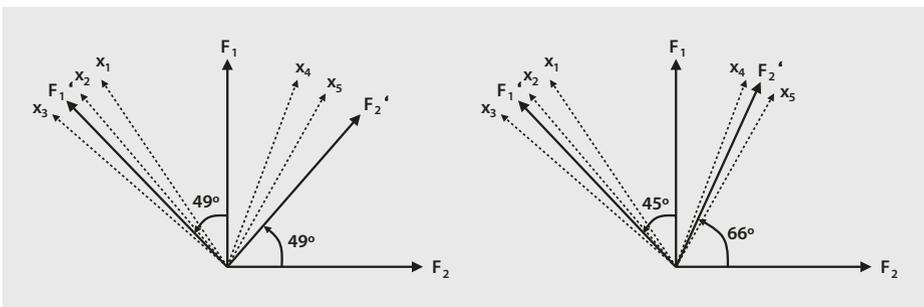
◘ **Fig. 8.6**   Orthogonal and oblique factor rotation

aims at maximizing the dispersion of loadings within factors, which means a few variables will have high loadings, while the remaining variables' loadings will be considerably smaller (Kaiser 1958)

Alternatively, we can choose between several **oblique rotation** techniques. In oblique rotation, the 90° angle between the factors is not maintained during rotation, and the resulting factors are therefore correlated. ◘ Figure 8.6 (right side) illustrates an example of an oblique factor rotation. **Promax rotation** is a commonly used oblique rotation technique. The promax rotation allows for setting an exponent (referred to as *kappa*) that needs to be greater than 1. Higher values make the loadings even more extreme (i.e., high loadings are amplified and weak loadings are reduced even further), which is at the cost of stronger correlations between the factors and less total variance explained (Hamilton 2013). A kappa value of 3 works well for most applications. **Direct oblimin rotation** is a popular alternative oblique rotation type, which allows specifying the maximum degree of obliqueness. This degree is the *delta*, which determines the level of the correlation allowed between the factors. A delta of zero (the default) ensures that the factors are—if at all—only moderately correlated, which is acceptable for most analyses. Oblique rotation is used when factors are possibly related. It is, for example, very likely that the respondents' satisfaction with the stadium is related to their satisfaction with other aspects of the soccer club, such as the number of stars in the team or the quality of the merchandise. However, relinquishing the initial objective of extracting uncorrelated factors can diminish the factors' interpretability. We therefore recommend using the varimax rotation to enhance the interpretability of the results. Only if the results are difficult to interpret, an oblique rotation should be applied. Among the oblique rotation methods, researchers generally recommend the promax (Gorsuch 1983) or oblimin (Kim and Mueller 1978) methods but differences between the rotation types are typically marginal (Brown 2009).

8.3.4.2 Assign the Variables to the Factors

After rotating the factors, we need to interpret them and give each factor a name, which has some descriptive value. Interpreting factors involves assigning each variable to a specific factor based on the highest *absolute* (!) loading. For example, if a variable has a 0.60 loading with the first factor and a 0.20 loading with the second, we would assign this variable to the first factor. Loadings may nevertheless be very similar (e.g., 0.50 for the first factor and 0.55 for the second one), making the assignment ambiguous. In such a situation, we could assign the variable to another factor, even though it does not have the highest loading on this specific factor. While this step can help increase the results' face validity (see ► Chap. 3), we should make sure that the variable's factor loading with the designated factor is above an acceptable level. If very few factors have been extracted, the loading should be at least 0.50, but with a high number of factors, lower loadings of above 0.30 are acceptable. Alternatively, some simply ignore a certain variable if it does not fit with the factor structure. In such a situation, we should re-run the analysis without variables that do not load highly on a specific factor. In the end, the results should be interpretable and actionable, but keep in mind that this technique is, first and foremost, exploratory!

8.3.5 Evaluate the Goodness-of-Fit of the Factor Solution

8.3.5.1 Check the Congruence of the Initial and Reproduced Correlations

While PCA focuses on explaining the variables' variances, checking how well the method approximates the correlation matrix allows for assessing the quality of the solution (i.e., the goodness-of-fit) (Graffelman 2013). More precisely, to assess the solution's goodness-of-fit, we can make use of the differences between the correlations in the data and those that the factors imply. These differences are also called **correlation residuals** and should be as small as possible.

In practice, we check the proportion of correlation residuals with an absolute value higher than 0.05. Even though there is no strict rule of thumb regarding the maximum proportion, a proportion of more than 50 % should raise concern. However, high residuals usually go hand in hand with an unsatisfactory KMO measure; consequently, this problem already surfaces when testing the assumptions.

8.3.5.2 Check How Much of Each Variable's Variance Is Reproduced by Means of Factor Extraction

Another way to check the solution's goodness-of-fit is by evaluating how much of each variable's variance the factors reproduce (i.e., the communality). If several communalities exhibit low values, we should consider removing these variables. Considering the variable-specific MSA measures could help us make this decision (see Box 8.1). If there are more variables in the dataset, communalities usually become smaller; however, if the factor solution accounts for less than 50 % of a variable's variance (i.e., the variable's communality is less than 0.50), it is worthwhile reconsidering the set-up.

8.3.6 Compute the Factor Scores

After the rotation and interpretation of the factors, we can compute the **factor scores**, another element of the analysis. Factor scores are linear combinations of the items and can be used as separate variables in subsequent analyses. For example, instead of using many highly correlated independent variables in a regression analysis, we can use few uncorrelated factors to overcome collinearity problems.

The simplest ways to compute factor scores for each observation is to sum all the scores of the items assigned to a factor. While easy to compute, this approach neglects the potential differences in each item's contribution to each factor (Sarstedt et al. 2016).

Drawing on the item weights produced by the PCA is a more elaborate way of computing factor scores (Hershberger 2005). These weights indicate each item's relative contribution to forming the factor; we simply multiply the standardized variables' values with the weights to get the factor scores. Factor scores computed on the basis of item weights have a zero mean. This means that if a respondent has a value greater than zero for a certain factor, he/she scores above the average in terms of the characteristic that this factor describes. Conversely, if a factor score is below zero, then this respondent exhibits the characteristic below average.

Different from the PCA, a factor analysis does not produce determinate factor scores. In other words, the factor is indeterminate, which means that part of it remains an arbitrary quantity, capable of taking on an infinite range of values (e.g., Grice 2001; Steiger 1979). Thus, we have to rely on other approaches to compute factor scores. The use of these approaches is, however, not restricted to factor analysis but extends to PCA, because of the specific way SPSS (and other programs) have implemented the method. The most prominent of these approaches is the **regression method**. This method takes into account (1) the correlation between the factors and variables (via the variable loadings), (2) the correlation between the variables, and (3) the correlation between the factors if oblique rotation has been used (DiStefano et al. 2009). The regression method z-standardizes each factor to zero mean and unit standard deviation.[5] We can therefore interpret an observation's score in relation to the mean and in terms of the units of standard deviation from this mean. For example, an observation's factor score of 0.79 implies that this observation is 0.79 standard deviations above the average with regard to the corresponding factor.

Another popular approach is the **Bartlett method**, which is similar to the regression method. In SPSS, the method produces factor scores with zero mean and standard deviations larger than one. Owing to the way they are estimated, the factor scores that the Bartlett method produces are considered more accurate (Hershberger 2005). However, in practical applications, both methods produce very similar results. Because of the z-standardization of the scores, which facilitates the comparison of scores across factors, we recommend using the regression method.

In ◘ Table 8.3 we summarize the main steps that need to be taken when conducting a PCA or factor analysis in SPSS.

8.4   Confirmatory Factor Analysis and Reliability Analysis

Many researchers and practitioners acknowledge the prominent role that exploratory factor analysis plays in exploring data structures. Data can be analyzed without preconceived ideas of the number of factors or how these relate to the variables under consideration. Whereas this approach is, as its name implies, exploratory in nature, the confirmatory factor analysis allows for testing hypothesized structures underlying a set of variables.

In a *confirmatory factor analysis*, the researcher needs to first specify the constructs and their associations with variables, which should be based on previous measurements or theory. Instead of allowing the procedure to determine the number of factors, as is done in an exploratory factor analysis, a confirmatory factor analysis tells us how well the actual data fit the pre-specified structure. Returning to our introductory example, we could, for example, assume that the construct *satisfaction with the stadium* can be measured by the three items x_1 (condition of the stadium), x_2 (appearance of the stadium), and x_3 (interior design of the stadium). Likewise, we could hypothesize that *satisfaction with the merchandise* can be adequately measured using the items x_4 and x_5. In a confirmatory factor analysis, we set up a theoretical model linking the items with the respective

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5   Note that this is only the case in PCA. When using factor analysis, the standard deviations are different from one (DiStefano et al. 2009).

▣ Table 8.3 Steps involved in carrying out a PCA or factor analysis in SPSS

Theory	Action
Check assumptions and carry out preliminary analyses	
Select variables that should be reduced to a set of underlying factors (PCA) or should be used to identify underlying dimensions (factor analysis)	► Analyze ► Dimension Reduction ► Factor. Enter the variables in the **Variables** box.
Are the variables interval or ratio scaled?	Determine the measurement level of your variables (see ► Chap. 3). If ordinal variables are used, make sure that the scale steps are equidistant.
Is the sample size sufficiently large?	Check MacCallum et al.'s (1999) guidelines for minimum sample size requirements, dependent on the variables' communality. For example, if all the communalities are above 0.60, small sample sizes of below 100 are adequate. With communalities around 0.50, sample sizes between 100 and 200 are sufficient. Ensure that your dataset meets these thresholds after handling missing values.
Are the observations independent?	Determine whether the observations are dependent or independent (see ► Chap. 3).
Are the variables sufficiently correlated?	► Analyze ► Dimension Reduction ► Factor ► Descriptives. Tick **Coefficients, Significance levels, KMO and Bartlett's test of sphericity**, and **Anti-image**. Check whether the KMO ≥ 0.50. Also consider the following measures: – Are the correlation coefficients different from zero and significant (indicated in the lower part of the correlation matrix under **Sig. (1-tailed)**)? – Is the *p*-value of the Bartlett's test (indicated by **Sig.**) ≤ 0.05? To identify items that are too lowly correlated, check the variable-specific MSA values (indicated in the **Anti-Image Correlation** table). Are the MSA values ≥ 0.50?
Extract the factors	
Choose the method of factor analysis	If the goal is to reduce the number of variables to a set of underlying factors (i.e., principal component analysis): ► Analyze ► Dimension Reduction ► Factor ► Extraction ► Principal components. If the goal is to identify underlying dimensions (i.e., factor analysis): ► Analyze ► Dimension Reduction ► Factor ► Extraction ►Principal axis factoring

⬛ **Table 8.3**   (Continued)

| Theory	Action
Determine the number of factors	
Determine the number of factors	Kaiser criterion: Extract all factor with an eigenvalue greater than 1 (default).
	Create a scree plot and select the number left of the distinctive break (elbow).
	► Analyze ► Dimension Reduction ► Factor ► Extraction ► Scree plot
	Run parallel analysis: Download the syntax file *Parallel analysis.sps* from the book's website (↓Web Appendix → Downloads) and open it in SPSS. Specify the number of observations under **compute Ncases** (line 10) and the number of variables under **compute NVars** (line 11). Go to ► Run ► All. Extract those factors whose original eigenvalues are greater than those indicated under **Prcntyle**.
	Pre-specify the number of factors based on a priori information: ► Analyze ► Data Reduction ► Factor ► Extraction ► Fixed number of factors: Factors to extract
	Check the **Cumulative %** column in the **Total Variance Explained** column.
Interpret the factor solution	
Rotate the factors	Use the varimax procedure or, if necessary, the promax procedure with kappa set to 3: ► Analyze ► Dimension Reduction ► Factor ► Rotation.
Assign variables to factors and interpret the factors	Use the rotated solution to assign each variable to a certain factor based on the highest absolute loading. To facilitate interpretation, you may also assign a variable to a different factor but check that the loading lies at an acceptable level (0.50 if only few factors are extracted, 0.30 if many factors are extracted).
	Find an umbrella term for clusters of items assigned to each factor.
Compute factor scores	Save factor scores as new variables using the regression method: ► Analyze ► Dimension Reduction ► Factor ► Scores ► Save as variables: Regression.
Evaluate the goodness-of-fit of the factor solution	
Check the congruence of the initial and reproduced correlations	Create a reproduced correlation matrix: ► Analyze ► Dimension Reduction ► Factor ► Descriptives ► Reproduced. Is the proportion of residuals greater than $0.05 \leq 50\,\%$?
Check how much of each variable's variance is reproduced by means of factor extraction	Examine the communalities from the reproduced correlation matrix. Check if reproduced communalities (on the diagonal) are ≥ 0.50.

construct (note that in confirmatory factor analysis, researchers generally use the term construct rather than factor). This process is also called operationalization (see ► Chap. 3) and usually involves drawing a visual representation (called a **path diagram**) indicating the expected relationships.

◘ Figure 8.7 shows a path diagram—you will notice the similarity to the diagram in ◘ Fig. 8.1. Ovals represent the constructs (e.g., Y_1, satisfaction with the stadium) and boxes represent the items (x_1 to x_5). Other elements include the relationships between the constructs and respective items (the loadings l_1 to l_5), the error terms (e_1 to e_5) that capture the extent to which a construct does not explain a specific item, and the correlations between the constructs of interest (r_{12}).

Having defined the individual constructs and developed the path diagram, we can estimate the model. The relationships between the constructs and items (the loadings l_1 to l_5) and the item correlations (not shown in ◘ Fig. 8.7) are of particular interest, as they indicate whether the construct has been reliably and validly measured.

Reliability analysis is an important element of a confirmatory factor analysis and essential when working with measurement scales. The preferred way to evaluate reliability is by taking two independent measurements (using the same subjects) and comparing these using correlations. This is also called **test-retest reliability** (see ► Chap. 3). However, practicalities often prevent researchers from surveying their subjects a second time.

An alternative is to estimate the **split-half reliability**. In the split-half reliability, scale items are divided into halves and the scores of the halves are correlated to obtain an estimate of reliability. Since all items should be consistent regarding what they indicate about the construct, the halves can be considered approximations of alternative forms of the
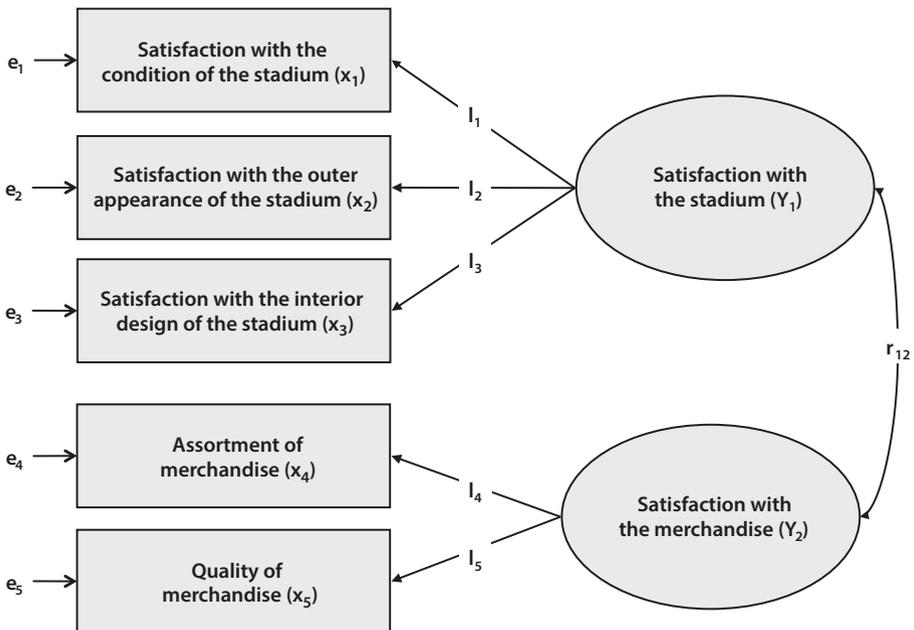
◘ **Fig. 8.7** Path diagram (confirmatory factor analysis)

> **Box 8.2 Things to consider when calculating Cronbach's Alpha**
>
> When calculating Cronbach's Alpha, ensure that all items are formulated in the same direction (positively or negatively worded). For example, in psychological measurement, it is common to use both negatively and positively worded items in a questionnaire. These need to be reversed prior to the reliability analysis. In SPSS, this can be achieved using the **Recode** option discussed in ► Chap. 5. Furthermore, we have to be aware of there being multiple factors in our item set. Some multi-item scales comprise subsets of items that measure different facets of a multidimensional construct. For example, soccer fan satisfaction is a multidimensional construct that includes aspects such as satisfaction with the stadium, the merchandise (as described above), the team, and the coach. Each of these factors is measured using different sets of items, whose consistency has to be evaluated separately. Calculating one Cronbach's Alpha over 99 items would certainly be inappropriate. Cronbach's Alpha is always calculated over the items belonging to one construct and not all items in the dataset!

same scale. Consequently, instead of looking at the scale's test-retest reliability, researchers consider the scale's equivalence, thus showing the extent to which two measures of the same general trait agree. We call this type of reliability the **internal consistency reliability**.

In the example of *satisfaction with the stadium*, we compute this scale's split-half reliability manually by, for example, splitting up the scale into x_1 on the one side and x_2 and x_3 on the other. We then compute the sum of x_2 and x_3 (or calculate the items' average) to form a total score and correlate this score with x_1. A high correlation indicates that the two subsets of items measure related aspects of the same underlying construct and, thus, suggests a high degree of internal consistency. However, with many items, there are many different ways to split the variables into two groups.

Cronbach (1951) proposed calculating the average of all possible split-half coefficients resulting from different ways of splitting the scale items. The **Cronbach's Alpha** coefficient has become by far the most popular measure of internal consistency. In the example above, this would comprise calculating the average of the correlations between (1) x_1 and $x_2 + x_3$, (2) x_2 and $x_1 + x_3$, as well as (3) x_3 and $x_1 + x_2$. The Cronbach's Alpha coefficient generally varies from 0 to 1, whereas a generally agreed lower limit for the coefficient is 0.70. However, in exploratory studies, a value of 0.60 is acceptable, while values of 0.80 or higher are regarded as satisfactory in the more advanced stages of research (Hair et al. 2011). In Box 8.2, we provide more advice on the use of Cronbach's Alpha. We will illustrate a reliability analysis using the standard SPSS module in the example at the end of this chapter.

8.5   Structural Equation Modeling

Whereas a confirmatory factor analysis involves testing if and how items relate to specific constructs, *structural equation modeling* involves the estimation of relations between these constructs. It has become one of the most important methods in social sciences, including marketing research.

There are broadly two approaches to structural equation modeling: **Covariance-based structural equation modeling** (e.g., Jöreskog 1971) and **partial least squares structural equation modeling** (e.g., Wold 1982), simply referred to as **CB-SEM** and **PLS-SEM**. Both estimation methods are based on the idea of an underlying model that allows the researcher to test relationships between multiple items and constructs.

■ Figure 8.8 shows an example path diagram with four constructs (represented by circles or ovals) and their respective items (represented by boxes).[6] A path model incorporates two types of constructs: (1) exogenous constructs (here, satisfaction with the stadium (Y_1) and satisfaction with the merchandise (Y_2)) that do not depend on other constructs, and (2) endogenous constructs (here, overall satisfaction (Y_3) and loyalty (Y_4)) that depend on one or more exogenous (or other endogenous) constructs. The relations between the constructs (indicated with p) are called path coefficients, while the relations between the constructs and their respective items (indicated with l) are the item loadings. One can distinguish between the structural model that incorporates the relations between the constructs and the (exogenous and endogenous) measurement models that represent the relationships between the constructs and their related items. Items that measure constructs are labeled x.

In the model in ■ Fig. 8.8, we assume that the two exogenous constructs *satisfaction with the stadium* and *satisfaction with the merchandise* relate to the endogenous construct *overall satisfaction* and that *overall satisfaction* relates to *loyalty*. Depending on the research question, we could of course incorporate additional exogenous and endogenous constructs. Using empirical data, we could then test this model and, thus, evaluate the relationships between all the constructs and between each construct and its items. We could, for example, assess which of the two constructs, Y_1 or Y_2, relates more strongly to Y_3. The result helps us when developing marketing plans to increase overall satisfaction and, ultimately, loyalty.

The evaluation of a path model analysis requires several steps that include the assessment of both measurement models and the structural model. Diamantopoulos and Siguaw (2000) and Hair et al. (2019) provide thorough descriptions of the covariance-based structural equation modeling approach and its application. Hair et al. (2017a, 2018) provide a step-by-step introduction on how to set up and test path models using partial least squares structural equation modeling.
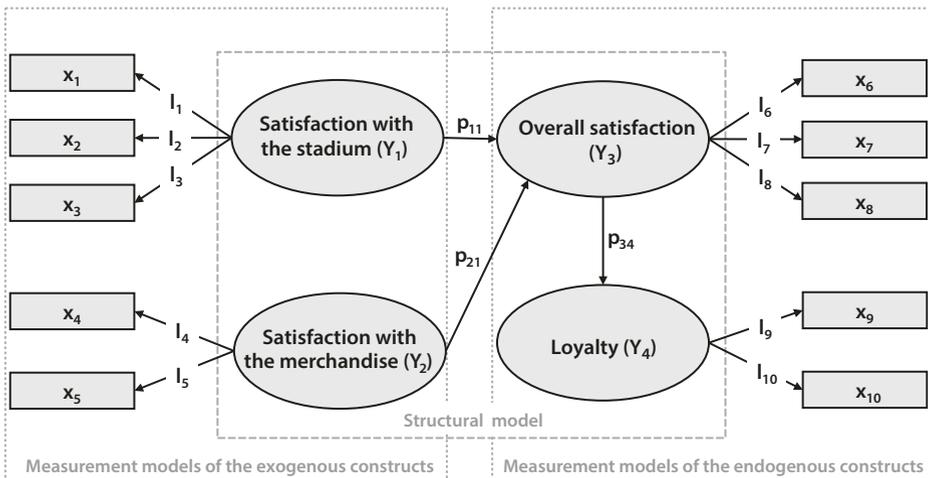
■ **Fig. 8.8** Path diagram (structural equation modeling)

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6   Note that we omitted the error terms for clarity.

8.6   **Example**

In this example, we take a closer look at some of the items from the Oddjob Airways dataset (↓ Web Appendix → Downloads). This dataset contains eight items that relate to the customers' experience when flying with Oddjob Airways. For each of the following items, the respondents had to rate their degree of agreement from 1 ("completely disagree") to 100 ("completely agree"). The variable names are included below:

- with Oddjob Airways you will arrive on time (s_1),
- the entire journey with Oddjob Airways will occur as booked (s_2),
- in case something does not work out as planned, Oddjob Airways will find a good solution (s_3),
- the flight schedules of Oddjob Airways are reliable (s_4),
- Oddjob Airways provides you with a very pleasant travel experience (s_5),
- Oddjob Airways's on board facilities are of high quality (s_6),
- Oddjob Airways's cabin seats are comfortable (s_7), and
- Oddjob Airways offers a comfortable on-board experience (s_8).

Our aim is to reduce the complexity of this item set by extracting several factors. Hence, we use these items to run a PCA.

8.6.1 **Principal Component Analysis**

8.6.1.1 **Check Requirements and Conduct Preliminary Analyses**

Before initiating the analysis, we need to check the assumptions of PCA and carry out preliminary analyses. We find that all eight variables are interval scaled from 1 ("very unsatisfied") to 100 ("very satisfied"), therefore meeting the requirements in terms of the measurement scale.

Determining whether the variables are sufficiently correlated is part of the PCA. To initiate the analysis, go to ► Analyze ► Dimension Reduction ► Factor. In the dialog box that opens (◘ Fig. 8.9), enter all eight variables into the **Variables** box.

Next, click on **Descriptives** (◘ Fig. 8.10) and check the boxes next to **Coefficients, Significance levels, Anti-image**, and **KMO and Bartlett's test of sphericity**. Also make sure to select **Reproduced**, which requests the reproduced correlation matrix that we will use for assessing the goodness-of-fit of the factor solution. Finally, select **Initial solution** and **Univariate descriptives** in the upper part of the dialog box to display useful summary statistics of your data. All other options are of minor importance, so skip these and click **Continue**.

Now click on **Extraction** (◘ Fig. 8.11) and choose **Principal components** in the **Method** drop-down menu. Under **Extract**, you can determine the rule for factor extraction. The default option in SPSS is the Kaiser criterion as indicated by the option **Eigenvalues greater than 1**. In case you have prior information regarding the number of factors to extract, select **Fixed number of factors** and specify the corresponding number next to **Factors to extract**. Finally, under **Display**, make sure to select **Unrotated factor solution** and **Scree plot**. Click on **Continue**.
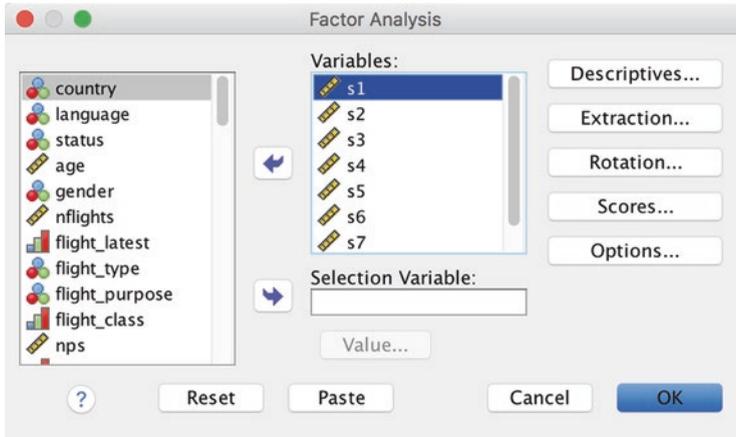
■ **Fig. 8.9** Factor analysis dialog box

■ **Fig. 8.10** Descriptives option
(factor analysis)
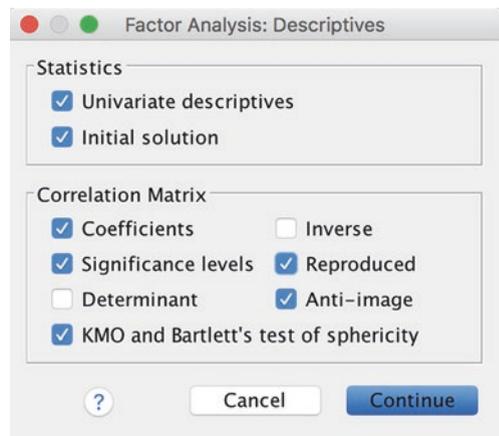
Under **Rotation**, you can choose between several orthogonal and oblique rotation methods. Select the **Varimax** procedure and click on **Continue**. Finally, under **Options**, you can decide how missing values should be handled and specify the display format of the coefficients in the component matrix. Select **Exclude cases listwise** to eliminate observations that have missing values in any of the variables used in any of the analyses. Avoid replacing missing values with the mean as this will diminish the variation in the data, especially if there are many missing values in your dataset. You should always check the option **Sorted by size** under **Coefficient Display Format**, as this greatly increases the clarity of the display of results. If you wish, you can suppress low loadings of say less than 0.20 by selecting the option **Suppress small coefficients**. Particularly when analyzing many items, this option makes the output much easier to interpret. After having specified all the options, you can initiate the analysis by clicking on **Continue**, followed by **OK**.
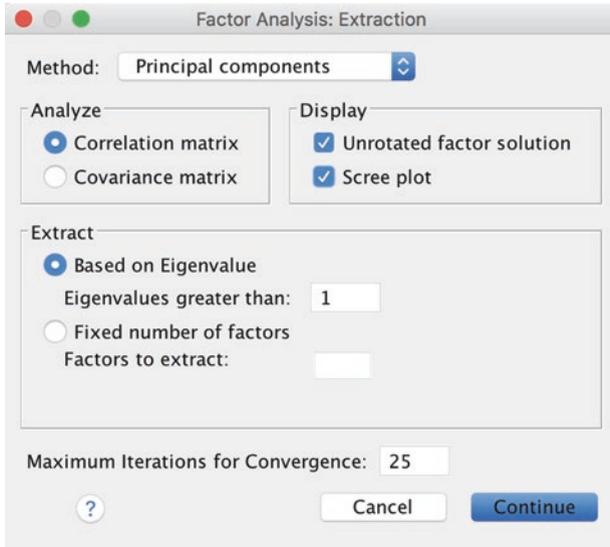
■ **Fig. 8.11**   Extraction option (factor analysis)

The descriptive statistics in ■ Table 8.4 reveal that there are several observations with missing values in the dataset. However, with **921** valid observations, the sample size requirements are clearly met, even if the analysis produces very low communality values.

The correlation matrix in the upper part of ■ Table 8.5 indicates that there are several pairs of highly correlated variables. The values in the diagonal are all **1.000**, which is logical, as this is the correlation between a variable and itself! The off-diagonal cells correspond to the pairwise correlations. For example, the pairwise correlation between s_1 and s_2 is **.754**. The corresponding value in the lower part of ■ Table 8.5 shows that all correlations are significant (**.000**). As an absolute minimum standard, we need at least one correlation in the off-diagonal cells to be significant and we clearly meet this minimum. The correlation matrix in ■ Table 8.5 also shows that there are several pairs of highly correlated variables. For example, not only s_1 is highly correlated with s_2 (correlation = **.754**), but also s_3 is highly correlated with s_1 (correlation = **.622**), just like s_4 (correlation = **.733**). As these variables' correlations with the remaining correlations is much lower, it is likely that these four variables form one factor. As you can see from the correlation matrix, we can already identify a likely factor structure.

The results in ■ Table 8.6 indicate a KMO value of **.907**, which is "marvelous" (■ Table 8.2). Correspondingly, all MSA values shown on the diagonal in the lower part of the **Anti-image Matrices** output (■ Table 8.7) are high. For example, s_1 has an MSA value of .914. Not surprisingly the Bartlett's test shown in ■ Table 8.6 is significant (**Sig. = .000**), which means that we can reject the null hypothesis of uncorrelated variables. Summarizing these results, we conclude that the data are appropriate for PCA. Hence, we can continue with the interpretation of the PCA.

�«■» **Table 8.4** Descriptive statistics

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
s1	60.36	26.300	921
s2	59.34	25.963	921
s3	55.83	25.150	921
s4	56.89	27.808	921
s5	56.48	22.269	921
s6	56.10	22.070	921
s7	51.60	24.568	921
s8	57.08	21.286	921

�«■» **Table 8.5** Correlation matrix

Correlation Matrix

		s1	s2	s3	s4	s5	s6	s7	s8
Correlation	s1	1.000	.754	.622	.733	.525	.500	.455	.542
	s2	.754	1.000	.697	.771	.536	.493	.453	.535
	s3	.622	.697	1.000	.648	.550	.492	.452	.553
	s4	.733	.771	.648	1.000	.484	.436	.367	.487
	s5	.525	.536	.550	.484	1.000	.818	.788	.811
	s6	.500	.493	.492	.436	.818	1.000	.832	.842
	s7	.455	.453	.452	.367	.788	.832	1.000	.780
	s8	.542	.535	.553	.487	.811	.842	.780	1.000
Sig. (1-tailed)	s1		.000	.000	.000	.000	.000	.000	.000
	s2	.000		.000	.000	.000	.000	.000	.000
	s3	.000	.000		.000	.000	.000	.000	.000
	s4	.000	.000	.000		.000	.000	.000	.000
	s5	.000	.000	.000	.000		.000	.000	.000
	s6	.000	.000	.000	.000	.000		.000	.000
	s7	.000	.000	.000	.000	.000	.000		.000
	s8	.000	.000	.000	.000	.000	.000	.000	

◨ **Table 8.6** KMO and Bartlett's test statistics

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.907
Bartlett's Test of Sphericity	Approx. Chi-Square	6421.354
	df	28
	Sig.	.000

8.6.1.2 Extract the Factors and Determine the Number of Factors

◨ Table 8.8 lists the eigenvalues associated with each factor before extraction, after extraction, and after rotation. In the columns labeled **Initial Eigenvalues**, we see the results before extraction. SPSS lists all eight factors (we know that there are potentially as many factors as there are variables) in this column. Most of these factors are only of minor importance. This is reflected in each factor's eigenvalue, which is displayed in the table's second column. Here, we see that the first factor has an eigenvalue of 5.249. As there are eight variables in our dataset, this factor accounts for 5.249/8.00 = 65.611 % of the overall variance, as indicated in the third column. It is quite remarkable that by using only one factor instead of eight variables, we can account for over 65 % of the overall variance! The second factor has an eigenvalue of 1.328 and, thus, still covers more variance than a single variable. In contrast, factors 3–8 only marginally account for the total variance explained, as their eigenvalues are considerably smaller than 1.

The second set of columns, labeled **Extraction Sums of Squared Loadings**, contains the factor solutions after extraction. Since we chose the Kaiser criterion as default option, SPSS extracts all factors with an eigenvalue greater than 1. As a consequence, SPSS extracts two factors, which jointly account for 82.215 % of the overall variance. The final part of the table, labeled **Rotation Sums of Squared Loadings**, displays the factors after rotation. The rotation typically changes the factors' eigenvalues, but not the total variance explained. For example, before rotation, the second factor accounted for 16.604 % of the overall variance but after rotation, it accounts for 39.582 %.

Looking at the scree plot in ◨ Fig. 8.12, we find an "elbow" in the line at three factors. As the number of factors that the scree plot suggests is one factor less than the elbow indicates, we conclude that two factors are appropriate. This finding therefore supports the conclusion as the Kaiser criterion.

While the Kaiser criterion and the scree plot are helpful for determining the number of factors to extract, parallel analysis is a more robust criterion. Parallel analysis can only be run using SPSS syntax. To do so, go to the book's ↓ Web Appendix (→ Downloads) and download the syntax file *Parallel analysis.sps* (O'Connor 2000). Next, go to ► File ► Open ►Syntax, locate the syntax file on your hard drive and open it. SPSS will now show the syntax editor as in ◨ Fig. 8.13.

Under **compute Ncases** in line 10, you need to specify the number of observations, which is **921** in our case study. Similarly, under **compute NVars** (line 11), specify the number

◘ Table 8.7 Anti-image matrices

Anti-image Matrices

		s1	s2	s3	s4	s5	s6	s7	s8
Anti-image Covariance	s1	.354	−.107	−.029	−.112	−8.946E−5	−.007	−.011	−.019
	s2	−.107	.289	−.102	−.122	−.009	−.001	−.013	.002
	s3	−.029	−.102	.440	−.066	−.036	.010	.004	−.036
	s4	−.112	−.122	−.066	.334	−.016	−.004	.037	−.011
	s5	−8.946E−5	−.009	−.036	−.016	.247	−.057	−.068	−.063
	s6	−.007	−.001	.010	−.004	−.057	.197	−.093	−.085
	s7	−.011	−.013	.004	.037	−.068	−.093	.262	−.040
	s8	−.019	.002	−.036	−.011	−.063	−.085	−.040	.226
Anti-image Correlation	s1	.917[a]	−.334	−.072	−.325	.000	−.025	−.035	−.068
	s2	−.334	.884[a]	−.285	−.393	−.034	−.003	−.049	.006
	s3	−.072	−.285	.943[a]	−.171	−.111	.034	.011	−.115
	s4	−.325	−.393	−.171	.883[a]	−.057	−.014	.125	−.039
	s5	.000	−.034	−.111	−.057	.931[a]	−.259	−.269	−.265
	s6	−.025	−.003	.034	−.014	−.259	.883[a]	−.408	−.400
	s7	−.035	−.049	.011	.125	−.269	−.408	.904[a]	−.164
	s8	−.068	.006	−.115	−.039	−.265	−.400	−.164	.918[a]

[a] Measures of Sampling Adequacy(MSA)

■ **Table 8.8** Factor extraction

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	5.249	65.611	65.611	5.249	65.611	65.611	3.411	42.633	42.633
2	1.328	16.604	82.215	1.328	16.604	82.215	3.167	39.582	82.215
3	.397	4.966	87.181						
4	.263	3.290	90.471						
5	.231	2.890	93.361						
6	.196	2.454	95.815						
7	.193	2.409	98.224						
8	.142	1.776	100.000						

Extraction Method: Principal Component Analysis.

Fig. 8.12 Scree plot

Fig. 8.13 Syntax editor

◼ **Fig. 8.14**   Parallel analysis output

```
Run MATRIX procedure:

Specifications for this Run:
Ncases      921
Nvars         8
Ndatsets   1000
Percent      95

Random Data Eigenvalues
          Root             Means        Prcntyle
    1.000000000    1.139664003    1.184621548
    2.000000000    1.088912224    1.121748890
    3.000000000    1.048871936    1.076347957
    4.000000000    1.014335675    1.036064920
    5.000000000     .981600330    1.004081100
    6.000000000     .948046716     .971752634
    7.000000000     .911595118     .940278387
    8.000000000     .866973997     .903115141

------ END MATRIX -----
```

of variables used in the analysis, which is **8**. Next, initiate the analysis by going to ► Run ► All and SPSS will show an output similar to ◼ Fig. 8.14.

The column labeled **Prcntyle** shows the 95th percentile for each factor's eigenvalue resulting from the randomly generated data. Note that because of this random process, your numbers are going to look different. However, deviations typically occur at the third decimal place. We can now compare the original eigenvalues from ◼ Table 8.8 with the randomly generated eigenvalues from ◼ Fig. 8.14. We learn that the first two factors produce eigenvalues larger than the randomly generated eigenvalues. Whereas the first original Eigenvalue is clearly higher (**5.249**; ◼ Table 8.7) than the randomly generated one (**1.185**; ◼ Fig. 8.14), the difference is much less pronounced for the second factor (**1.328** vs. **1.122**). The third factor's original eigenvalue (**.397**) is clearly lower than its randomly generated counterpart (**1.076**). Hence, based on the parallel analysis results, we would also opt for a two-factor solution.

8.6.1.3 Interpret the Factor Solution

We continue with the interpretation of the factors. To do so, take a look at **the Rotated Component Matrix** (◼ Table 8.9), which shows the item loadings after rotation. To interpret the factors, we first "assign" each variable to a certain factor based on its maximum absolute factor loading. That is, if the highest absolute loading is negative, higher values of a particular variable relate negatively to the assigned factor. After that, we should find a label for each factor that best describes the set of variables associated with that factor. Looking at ◼ Table 8.9, we see that s_1–s_4 load highly on the second factor, whereas s_5–s_8 load on the first factor. For example, s_1 has a **.829** loading on the second factor, while its loading is much weaker on the first factor (**.299**). If you compare these results with the regular **Component Matrix**, you will see that prior to rotation, all items load highly on the first factor and much weaker on the second.

Having identified which variables load highly on which factor in the rotated solution, we now need to identify labels for each factor. Looking at the variable labels, we learn

◘ **Table 8.9** Rotated component matrix

Rotated Component Matrix[a]

	Component	
	1	2
s6	.903	.272
s7	.902	.208
s8	.856	.352
s5	.852	.347
s4	.198	.885
s2	.282	.871
s1	.299	.829
s3	.340	.759

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
[a] Rotation converged in 3 iterations.

that the first set of variables (s_1–s_4) relate to reliability aspects of the journey and related processes, such as the booking. We could therefore label this factor (i.e., factor 2) *reliability*. The second set of variables (s_5–s_8) relate to different aspects of the onboard facilities and the travel experience. Hence, we could label this factor (i.e., factor 1) *onboard experience*. The labeling of factors is subjective and you could provide different labels.

8.6.1.4 **Evaluate the Goodness-of-Fit of the Factor Solution**

The last step involves assessing the analysis's goodness-of-fit. To do so, we first look at the residuals (i.e., the differences between observed and reproduced correlations) in the reproduced correlation matrix (◘ Table 8.10). Examining the lower part of the table, we see that there are several residuals with absolute values larger than 0.05. However, we do not have to count every single value in the matrix (this could be quite exhausting if there are over 100 variables in the dataset!). Instead, SPSS counts the proportion of residuals with high residuals, which is reported in the first part of the table. As we can see in point b beneath the table, 28.0 % of the residuals have absolute values greater than 0.05. As the percentage of increased residuals is well below 50 %, we can presume a good model fit.

This result is supported by the variables' communalities and the total variance explained. All communalities in ◘ Table 8.11 are very high, indicating that the factors reproduce the variables' variance well. For example, with a value of **.763**, s_1 has a communality value clearly above the 0.50 threshold, suggesting that the two factors account for 76.3 % of this variable's variation. Finally, the two factors explain over 80 % of each variable's variance (◘ Table 8.8). Jointly these results provide support for the solution's goodness-of-fit.

❯ **In case the analysis indicates a poor goodness-of-fit, you should reconsider the set-up by eliminating items that have low communalities and MSA values.**

8

Table 8.10 Reproduced correlations and residual matrices

Reproduced Correlations

		s1	s2	s3	s4	s5	s6	s7	s8
Reproduced Correlation	s1	.777[a]	.806	.731	.793	.542	.495	.442	.548
	s2	.806	.838[a]	.757	.827	.542	.491	.435	.548
	s3	.731	.757	.691[a]	.739	.553	.513	.464	.558
	s4	.793	.827	.739	.822[a]	.476	.420	.363	.482
	s5	.542	.542	.553	.476	.847[a]	.864	.840	.852
	s6	.495	.491	.513	.420	.864	.890[a]	.871	.869
	s7	.442	.435	.464	.363	.840	.871	.856[a]	.845
	s8	.548	.548	.558	.482	.852	.869	.845	.856[a]
Residual[b]	s1		-.053	-.109	-.060	-.017	.005	.014	-.006
	s2	-.053		-.060	-.056	-.006	.002	.018	-.013
	s3	-.109	-.060		-.091	-.003	-.022	-.012	-.006
	s4	-.060	-.056	-.091		.008	.016	.004	.005
	s5	-.017	-.006	-.003	.008		-.046	-.053	-.040
	s6	.005	.002	-.022	.016	-.046		-.039	-.026
	s7	.014	.018	-.012	.004	-.053	-.039		-.065
	s8	-.006	-.013	-.006	.005	-.040	-.026	-.065	

Extraction Method: Principal Component Analysis.

[a] Reproduced communalities

[b] Residuals are computed between observed and reproduced correlations. There are 8 (28.0 %) nonredundant residuals with absolute values greater than 0.05.

◫ **Table 8.11** Communalities

Communalities

	Initial	Extraction
s1	1.000	.777
s2	1.000	.838
s3	1.000	.691
s4	1.000	.822
s5	1.000	.847
s6	1.000	.890
s7	1.000	.856
s8	1.000	.856

Extraction Method: Principal Component Analysis.

8.6.1.5 Compute the Factor Scores

If you wish to use factor scores in subsequent analyses, you can rerun the analysis by going to ► Analyze ► Dimension Reduction ► Factor and selecting the **Scores** option. Since we recommend using the regression method, choose **Save as variables** and **Regression**. When clicking on **Continue** and **OK**, SPSS creates two new variables labeled *FAC1_1* and *FAC2_1*, which include the scores of the two factors (◫ Fig. 8.15). These are *z*-standardized, meaning that the newly generated variables have mean values of 0 and standard deviations of 1. This entails the factor scores are estimated in units of standard deviations from their means. For example, the first observation is about **1.911** standard deviations below average on the *onboard experience* factor (i.e., factor 1) and about **0.914** standard deviations above the *reliability* factor (i.e., factor 2). In contrast, the second observation is clearly above average in terms of *onboard experience* (**1.684**) and *reliability* (**1.297**). Using these variables as input we could, for example, evaluate whether male and female customers differ significantly with regard to their satisfaction with the airline's reliability, and the onboard experience.

🛇 **SPSS can only calculate factor scores if it has information on all the variables included in the analysis. If SPSS does not have all the information, it only shows a "." (dot) in the data view window, indicating a system-missing value.**

8.6.2 Reliability Analysis

To illustrate its usage, let's carry out a reliability analysis of the first factor *onboard experience* by calculating Cronbach's Alpha as a function of variables s_5 to s_8. To run the reliability analysis, click on ► Analyze ► Scale ► Reliability Analysis. Next, enter variables s_5, s_6, s_7, and s_8 into the **Items** box (again, you may have to right-click on the items and select **Display Variable Names** to show the names instead of the variable labels) and type in the

	commitment	FAC1_1	FAC2_1
1	1,67	−1,91122	,91449
2	7,00	1,68442	1,29712
3	1,00	−2,43278	,44368
4	7,00	,16654	,84207
5	3,67	−,12045	−,85245
6	4,00	−,47050	,39936
7	1,00	,82717	−1,99025
8	5,33	,20479	,90546
9	4,00	,48860	1,04368
10	1,33	,52727	−,70655

◘ **Fig. 8.15**   SPSS data view window

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scale's name (e.g., *satisfaction with the onboard experience*). Make sure that **Alpha** is selected in the **Model** drop-down list (◘ Fig. 8.16).

Next, click on **Statistics** and choose **Scale if item deleted** (◘ Fig 8.17). You can also request several descriptive statistics for each item (including correlations) and the entire scale. However, for the sake of simplicity, we will work with the default settings. Click on **Continue**, followed by **OK**.

The results in ◘ Table 8.12 show that the scale exhibits a high degree of internal consistency reliability. With a value of **.944**, the Cronbach's Alpha coefficient lies well above the commonly suggested threshold of .70. This result is not surprising, since we are simply testing a scale previously established using item correlations. Keep in mind that we should
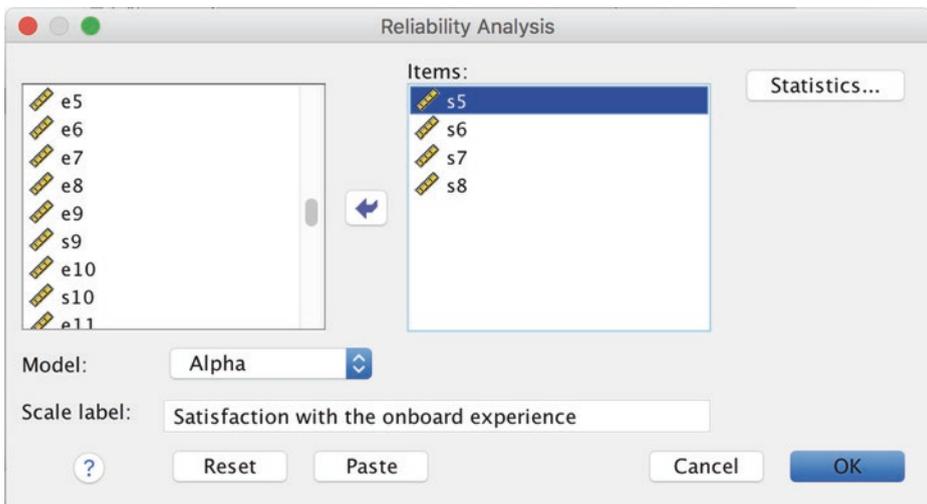

◘ **Fig. 8.16**   Reliability analysis dialog box

◘ **Table 8.12** Reliability statistics

Reliability Statistics

Cronbach's Alpha	No of Items
.944	4

carry out a reliability analysis to test a scale using a different sample—this example is only for illustration purposes! The rightmost column of ◘ Table 8.13 indicates what the Cronbach's Alpha would be if we deleted the item indicated in that row. When we compare each of the values with the overall Cronbach's Alpha value, we can see that any change in the scale's set-up would reduce the Cronbach's Alpha value. For example, by removing s_5 from the scale, the Cronbach's Alpha of the new scale comprising only s_6, s_7, and s_8 would be reduced to **.928**. In the column labeled **Corrected Item-Total Correlation** of ◘ Table 8.13, SPSS indicates the correlation between the item and the scale that is composed of other items. This information is useful for determining whether reverse-coded items were also identified as such. Reverse-coded items should have a minus sign.

◘ **Table 8.13** Item-total statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
s5	165.53	4084.951	.861	.928
s6	165.91	4045.200	.896	.917
s7	170.42	3859.797	.852	.933
s8	164.96	4215.151	.861	.929

◘ **Fig. 8.17** Statistics option (reliability analysis)

8.7   Customer Satisfaction at Haver & Boecker (Case Study)

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Haver & Boecker (http://www.haverboecker.com) is one of the world's leading and most renowned machine producers in the fields of mineral processing, as well as the storing, conveying, packing, and loading of bulk material. The family-owned group operates through its global network of facilities, with manufacturing units, among others, in Germany, the UK, Belgium, US, Canada, Brazil, China, and India.
The company's relationships with its customers are usually long-term oriented and complex. Since the company's philosophy is to help customers and business partners solve their challenges or problems, they often customize their products and services to meet the buyers' needs. Therefore, the customer is not a passive buyer, but an active partner. Given this background, the customers' satisfaction plays an important role in establishing, developing, and maintaining successful customer relationships. Early on, the company's management realized the importance of customer satisfaction and decided to commission a market research project in order to identify marketing activities that can positively contribute to the business's overall success. Based on a thorough literature review, as well as interviews with experts, the company developed a short survey to explore their customers' satisfaction with specific performance features and their overall satisfaction. All the items were measured on seven-point scales, with higher scores denoting higher levels of satisfaction.

A standardized survey was mailed to customers in 12 countries worldwide, which resulted in 281 fully completed questionnaires. The following items (names in parentheses) were listed in the survey:

- Reliability of the machines and systems. (s_1)
- Life-time of the machines and systems. (s_2)
- Functionality and user-friendliness operation of the machines and systems. (s_3)
- Appearance of the machines and systems. (s_4)
- Accuracy of the machines and systems. (s_5)
- Timely availability of the after-sales service. (s_6)
- Local availability of the after-sales service. (s_7)
- Fast processing of complaints. (s_8)
- Composition of quotations. (s_9)
- Transparency of quotations. (s_{10})
- Fixed product prize for the machines and systems. (s_{11})
- Cost/performance ratio of the machines and systems. (s_{12})

- Overall, how satisfied are you with the supplier? (*overall*)

Your task is to analyze the dataset to provide the management of Haver & Boecker with advice for effective customer satisfaction management. The dataset is labeled *Haver and Boecker.sav* (↓ Web Appendix → Downloads).

1. Using regression analysis, locate those variables that best explain the customers' overall satisfaction (*overall*). Evaluate the model fit and assess the impact of each variable on the dependent variable. Remember to consider collinearity diagnostics.

2. Determine the factors that characterize the respondents using factor analysis. Use items s_1–s_{12} for this. Run a PCA with varimax rotation to help interpretation. Consider the following aspects:
   (a) Are all assumptions for carrying out a PCA met? Are the data are sufficiently correlated?
   (b) How many factors would you extract? Base your decision on the Kaiser criterion, the scree plot, and parallel analysis. Do these three methods suggest the same number of factors?
   (c) Find suitable labels for the extracted factors.
   (d) Evaluate the factor solution's goodness-of-fit.

3. Use the factor scores and regress the customers' overall satisfaction (*overall*) on these. Evaluate the strength of the model and compare it with the initial regression. What should Haver & Boecker's management do to increase their customers' satisfaction?

4. Calculate the Cronbach's Alpha over items s_1–s_5 and interpret the results.

For further information on the dataset and the study, see Festge and Schwaiger (2007), as well as Sarstedt et al. (2009).

8.8   Review Questions

1. What is factor analysis? Try to explain what factor analysis is in your own words.
2. What is the difference between exploratory factor analysis and confirmatory factor analysis?
3. What is the difference between PCA and factor analysis?
4. Describe the terms communality, eigenvalue, and factor loading. How do these concepts relate to one another?
5. Describe the Kaiser criterion, the scree plot, and parallel analysis to determine the number of factors. What are there similarities and differences between these methods?

6.　What is the purpose of a varimax rotation? Does a rotation alter eigenvalues or factor loadings?
7.　Re-run the Oddjob Airways case study by carrying out a factor analysis and compare the results to the PCA analysis described in ▶ Sect. 8.6. Are there any differences?
8.　What is reliability analysis and why is it important?
9.　Explain the basic principle of structural equation modeling.

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