Chapter 14
Multilevel Simultaneous Component Analysis for Studying Intra-Individual Variability and Inter-Individual Differences

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In psychology, the distinction between traits and states has become commonplace for a long time: Whereas traits pertain to person features that are relatively stable and consistent, states refer to person features that fluctuate across time, for example as a result of situational influences. For instance, Allport and Odbert (1936) provided an extensive list of trait and state terms to characterize personality and personal behavior. The trait terms describe permanent, consistent dispositions and were considered to 'symbolize most clearly "real" traits of personality' (Allport & Odbert, 1936, p. 26). The state terms describe 'Temporary Moods or Activities'. They were not considered to symbolize personality, and were merely included for the sake of completeness.

Also in emotion research, the differences between emotional traits and states are studied, for the broad categories of positive and negative emotions as well as for specific emotions like anxiety (Spielberger, 1972) and gratitude (Wood, Maltby, Stewart, Linley, & Joseph, 2008). Herewith, an important topic of debate is the nature of the relations between different emotions at the trait and state levels. For example, it appears to be agreed upon that positive and negative emotional traits are independent across individuals; however, at the state level, both an independency (Watson & Clark, 1994; Zevon & Tellegen, 1982) and a negative relationship between positive and negative emotional states have been reported (Vansteelandt, Van Mechelen, & Nezlek, 2005).

Research on traits and states typically involve repeated measurements of individuals on a number of variables, like personality-related characteristics or emotions. To obtain a proper understanding of traits and states aspects of these variables, there is a need for statistical methods that allow to unravel these trait and states aspects. This chapter deals with such a method, which models multivariate data that have been repeatedly gathered from more than one individual in an exploratory way. The key idea of this method is the following: the scores of each single individual on the

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variables will show variability over the measurements. The goal of our modeling is to identify meaningful sources of the intra-individual variability in the observed variables, and to investigate whether and how the sources of intra-individual variability differ across individuals. Additionally, we will have a look at sources of inter-individual variability.

The repeated measurements within individuals may pertain to different measurement occasions, like in a diary design, when data are daily gathered. However, the repeated measurements of an individual may also pertain to different circumstances, conditions, or target persons. Because the modeling focuses on intra-individual variability, it is not necessary to have comparable measurements across individuals, like the same conditions or target persons.

To identify the sources of intra-individual and inter-individual variability, we use multilevel simultaneous component analysis (MLSCA; Timmerman, 2006). As a start, a component model for a single individual only is presented.

Subsequently, the MLSCA approach to a simultaneous modeling of the multivariate repeated measures data of a number of individuals is introduced. The empirical value of MLSCA is compared to its counterparts in Structural Equation Modeling. The use of the MLSCA model to gain insight into intra-individual and inter-individual variability is illustrated by two empirical examples. The chapter closes by some concluding remarks.

Principal Component Analysis of Single Subject Multivariate Data

An early approach to study the structure in a multivariate data set from a single individual is the P-technique (Cattell, 1952), which is a factor analysis of the correlations between variables, computed over repeated measurements. In various P-technique applications different factor analysis types were used (see Jones & Nesselroade, 1990), among which Principal Component Analysis (PCA). Component analysis is a data reduction technique that summarizes a number of observed variables into a smaller number of components by making linear combinations of the observed variables. PCA searches the components such that they explain as much of the variance in the data as possible. PCA is commonly applied to scores on a number of variables obtained from a number of individuals, but can be applied equally well to scores obtained from an individual at repeated measurements. Assuming that the scores of a single individual on J variables at K repeated measurements are collected in data matrix $\mathbf{Y}$ ($K \times J$), such a PCA analyzes either the covariance or the correlation structure of the variables. In the latter case, the data matrix is columnwise standardized before analysis, i.e., the variables are rescaled to have variances equal to one. As a consequence, all variables are equally weighted in the PCA. A PCA decomposes the (raw or standardized) data matrix $\mathbf{Y}$ as

$$\mathbf{Y} = \mathbf{1}_K \mathbf{m}' + \mathbf{F}\mathbf{B}' + \mathbf{E}, \tag{1}$$

where the apostrophe indicates the transpose operator, $\mathbf{1}_K$ is the $K \times 1$ vector with each element equal to one, $\mathbf{m}$ ($J \times 1$) is the vector containing the means of the J variables across measurements, $\mathbf{F}$ ($K \times Q$) denotes the matrix that contains the scores of the repeated measurements on the Q principal components, $\mathbf{B}$ ($J \times Q$) indicates the loading matrix, and $\mathbf{E}$ ($K \times J$) is the residual matrix; the principal components in $\mathbf{F}$ are uncorrelated, and have variances equal to one. The data matrix $\mathbf{Y}$ is decomposed in a way that maximizes the explained variance in the observed data given a fixed value of Q, which is equivalent to minimizing the sum of squared residuals.

The interpretation of a PCA solution is based on the loading matrix. The relative size of the loading of a variable on a component indicates to what extent the variable is associated to that component. A high loading is either high positive or low negative, whereas a low loading is near zero. When standardized data are decomposed, the relative size of the loadings is immediately clear, because then the loadings are correlations between variables and components. Variables with relatively high loadings on a particular component are associated strongly to that component, and hence are summarized well by this very component, whereas variables with low loadings are summarized badly. To interpret the components, the content of the well-summarized variables is examined.

To ease the interpretation of a PCA solution, it is common to rotate the loading matrix towards a more simple structure, for example using the popular Varimax rotation (Kaiser, 1958). Simple structure loadings are such that per component each loading is either high or low. Such a rotation does not alter the sum of squared residuals, provided that the rotation is compensated by counterrotating the scores on the principal components. The resulting components are orthogonal (uncorrelated) or oblique (correlated), depending on the rotation applied. A component score indicates the relative degree of the particular property that is indicated by the component concerned. To investigate the individual's behavior on the various components, the series of component scores for each component can be plotted against time. In such a plot, possible trends and outliers at certain occasions can be seen at once.

For example, the variables may pertain to emotions, like satisfied, happy, love, and affection. An individual may indicate to what extent he experienced those emotions on a large number of consecutive days. A PCA of the resulting data followed by (orthogonal) Varimax rotation may reveal two components, where the first component shows a clustering of the variables satisfied and happy, and the second component a clustering of the variables love and affection. Those components could be interpreted as General Positive Emotion (PE) and Interpersonal PE. The experience of emotions that belong to the same cluster highly covaries across time, so that at a particular measurement occasion, the relative strength of these emotions is similar. The two components General PE and Interpersonal PE are uncorrelated, implying that the relative strength of General PE at a particular measurement is unrelated to Interpersonal PE. By plotting the component scores on General or Interpersonal PE against time, one can examine how those emotions evolve over time.

Approaches to Analyzing Multivariate Data of Multiple Subjects

For a single individual, PCA can be used to identify meaningful sources of the intra-individual variability in the observed variables. However, the primary research interest usually pertains to characterizing a group of individuals, rather than a single individual. By studying more than one individual repeatedly, the way opens to compare the sources of intra-individual variabilities across individuals.

To study the intra-individual variability in multivariate data of a number of individuals, one may adopt different modeling strategies. Firstly, one may assume that the individuals stem from a homogeneous population. This means that they do not differ on the parameters of interest that express the intra-individual variability. The linear dynamic model for multiple subjects (Bijleveld & Bijleveld, 1997) and chain P-technique are based on this very convenient, but often unrealistic, assumption. Chain P-technique simply involves a factor analysis of the aggregated repeated multivariate data sets over subjects, and is rather often applied (e.g., Hurlburt, Lech, & Saltman, 1984; Reise, Ventura, Nuechterlein, & Kim, 2005). Nesselroade and Molenaar (1999) proposed a formal test procedure to find subsample(s) of subjects for which aggregation is reasonable. Still, the approach is somewhat unsatisfactory. The individuals in the selected subsample may still have interesting intra-individual differences, which will be kept hidden using this approach. Furthermore, comparing homogeneous subsamples may be rather tedious.

A second approach to analyzing the data from more than one individual is opposite to the aggregating approach, in that the data of each individual are factor analyzed separately (see Jones & Nesselroade, 1990). Clearly, this approach offers ample opportunities to cover the intra-individual variability. However, the price to be paid is an increase in difficulty to gain insight into similarities and differences across individuals.

When judging the similarities in intra-individual structure, it is common to compare the individual's loading matrices, either by eye or using some quantitative measure, as the congruence coefficient (Tucker, 1951). When the loading matrices are about equal, the intra-individual structure is apparently stable across subjects. Moreover, because the components are defined in (about) the same way, the component scores at the repeated measurements (or characteristics thereof, like the autoregressive structure) can be compared across individuals. Serious troubles arise when the comparison fails to find evidence for equal loading matrices. The dissimilarities may result from arbitrary differences in axes orientation of the loadings. This can be solved by optimally rotating the loading matrices towards each other, using a Procrustes approach (see Gower & Dijksterhuis, 2004). A more fundamental problem than the one with orientation differences is, that dissimilarities between loading matrices can always be resolved by considering more components per individual (Ten Berge, 1986). Therefore, Ten Berge (1986) argued that one should question the amount of variance explained by comparable components over individuals, rather than the degrees of similarity between loadings.

Another disadvantage of separate factor analyses is that individual differences in variances across measurements are not expressed properly, irrespective of whether the factor analysis is based on covariance or correlation matrices. This is unfortunate as those differences reflect the individuals' relative stability in scores across repeated assessments. When the individuals' covariance matrices are being factor analyzed separately and the factors are standardized with variance equal to one (as is commonly done), individual differences in variances show up in the relative sizes of the loadings. However, this complicates comparisons across individuals, as the differences in relative loading sizes also reflect difference in structure. When individuals' correlation matrices are being analyzed, individual differences in variances are even completely lost.

A third approach to analyzing multivariate repeated measures data from more than one individual is intermediate to the previous two, namely a simultaneous analysis of the data sets of the different individuals. This Simultaneous Component Analysis (SCA; Timmerman & Kiers, 2003) covers both the similarities and differences in intra-individual variability. The key idea of SCA is to decompose the data of each individual into a few components, and a single loading matrix, which is common to all individuals. The common loading matrix ensures comparability across individuals. The amount of variance explained per component can be compared across individuals to assess the relative importance of this component. Furthermore, the (co)variances of individual components provide a basis to compare the relative degree of intra-individual variability across individuals, as will be discussed in Section "Sources of Intra-Individual Variability in the MLSCA Model".

Because SCA is applied to unravel the sources of intra-individual variability of a number of individuals, SCA models the within-part of the data. The within-part of the data of each individual is estimated by subtracting the means of the variables across measurements from the observed data, i.e., by centering the data within each individual. This approach is also custom when a PCA on a single data set is performed (see Eq. 1), where the data reduction takes place on the within-part of the data. However, the total variability in repeated measures data of a number of individuals usually is due to both intra-individual variability, and to variability between individuals. The part of the data due to inter-individual variability will be denoted by the between-part. For each individual, the between-part of each variable is being estimated as the mean of the variable at hand across the measurements. Analogously to the within-part, the inter-individual variability of multivariate data may stem from only a few sources, which can also be explored with a component analysis. The full component analysis of both the between- and within-parts of the data is accommodated into one component analysis, which is denoted as multilevel simultaneous component analysis (MLSCA; Timmerman, 2006). The MLSCA model will be presented in some detail in the next section.

MLSCA of Multivariate Data of Multiple Individuals

Suppose that the scores of individual i on J variables at K_i repeated measurements are collected in data matrix $\mathbf{Y}_i$ ($K_i \times J$), and that data matrices are available for I individuals. As is well known from analysis of variance, the total variance of each variable can be written as the sum of the variances of the between- and within-parts. MLSCA searches between- and within-components such that they explain as much as possible of the variance in the between- and within-part, respectively. In an MLSCA, the data matrices $\mathbf{Y}_i$ ($i=1,\ldots,I$) of the I individuals are decomposed as

$$\mathbf{Y}_i = \mathbf{1}_{K_i}\mathbf{m}' + \mathbf{1}_{K_i}\mathbf{f}'_{ib}\mathbf{B}'_b + \mathbf{F}_{iw}\mathbf{B}'_w + \mathbf{E}_i, \tag{2}$$

where $\mathbf{1}_{K_i}$ is the $K_i \times 1$ vector with each element equal to one, $\mathbf{m}$ ($J \times 1$) is the vector containing the means of the J variables across all individuals and measurements. The between-part of the data is modeled by $\mathbf{f}_{ib}$ ($Q_b \times 1$), the vector with between-component scores of individual i, and $\mathbf{B}_b$ ($J \times Q_b$), the between-loading matrix, where Q_b denotes the number of between-components. The individuals' between-component scores $\mathbf{f}_{ib}'$, $i=1,\ldots,I$, can be conveniently arranged in the matrix $\mathbf{F}_b$ ($I \times Q_b$). The within-part of the data is modeled by $\mathbf{F}_{iw}$ ($K_i \times Q_w$), the matrix containing the within-component scores on measurements 1 to K_i of individual i, and $\mathbf{B}_w$ ($J \times Q_w$), the within-loading matrix, where Q_w denotes the number of within-components. $\mathbf{E}_i$ ($K_i \times J$) denotes the matrix of residuals of individual i. The mean between-component scores across individuals are constrained to zero (i.e., $\sum_{i=1}^{I} K_i\mathbf{f}_{ib} = \mathbf{0}_{Qb}$), which is sufficient to assure that the overall mean, the between-part and the within-part of the model are uniquely separated. Per individual, the mean within-component scores across measurements are zero (hence, $\mathbf{1}'_{k_i}\mathbf{F}_{iw} = \mathbf{0}'_{Q_W}$, $i=1,\ldots,I$); the variances of between- and within component scores are fixed to one. The (co)variances of the within-component scores may be restricted, yielding four different MLSCA variants, as will be discussed in Section "Sources of Intra-Individual Variability in the MLSCA Model".

Given fixed values for the numbers of between- and within-components (Q_b and Q_w, respectively), the MLSCA model is fitted to observed data matrices by minimizing the sum of squared residuals (Timmerman, 2006). The fitting procedure boils down to two separate component analyses, namely a weighted PCA to the between-part, and an SCA to the within-part of the data.

When it is desirable that all variables equally influence the MLSCA solution, the data should be standardized prior to analysis, by rescaling the variance to one per variable over individuals and measurements. Note that standardizing per individual across measurements is not wise, as possible differences across individuals in intra-individual variability are eliminated. An advantage of standardization is that both the between- and within-loadings are correlations between components and variables. Also, for each variable, the proportion of variance explained by the between- or within-components can be immediately derived, namely as the squared between- or within-loadings, respectively.

Sources of Intra-Individual Variability in the MLSCA Model

In MLSCA, the SCA model of the within-part expresses the intra-individual variability. The SCA model consists of a within-loading matrix, and within-component scores matrices of the individuals. The within-loading matrix expresses which variables cluster across measurements, i.e., which variables have similar relative scores at the measurements. As gently explained by Nesselroade (2007), the intra-individual structure may differ to some extent across individuals. To have a full understanding of the intra-individual structures of different individuals, it is important to properly express their similarities and differences. This is regulated in the SCA model by imposing constraints on the (co)variances of the within-component scores, yielding four SCA variants. Ordered from the most to least constrained, the four SCA variants are: SCA-ECP, with both covariances and variances equal across individuals; SCA-IND, with zero covariances and free variances; SCA-PF2 with equal covariances and free variances, and MLSCA-P, with both covariances and variances free across individuals. The loading matrices of SCA-ECP and SCA-P solutions have transformational freedom, just like in PCA, which can be exploited to facilitate the interpretation. In contrast, SCA-IND and SCA-PF2 solutions are uniquely estimated in practice, up to permutation and reflection of the components.

What do differences in (co)variances of within-component scores across individuals tell about inter-individual differences in intra-individual structure? The *variances* express the relative degree of intra-individual variability of the corresponding components. Thus, individual differences in within-component variances imply different degrees of stability across measurements on this very component. Those differences are allowed for in the SCA-IND, SCA-PF2 and SCA-P models. In the most extreme case, such a variance may be (close to) zero for one or more individuals, implying that this within-component is of hardly any relevance at all for those individuals. When the *raw* data of the latter individuals would have been analyzed separately by a PCA, this component would not have been found. On the contrary, a PCA of the *standardized* data could possibly result in this component. However, the status of this component is questionable. After all, it is based on variables of which the variability is artificially inflated.

The *covariances* between the within-components express their mutual degree of linear dependence. Thus, differences in within-component covariances mean that the degree of linear dependence may vary across individuals; this is allowed for in the SCA-P model only. To interpret the strength of those linear dependencies, it is convenient to consider the individuals' correlations between within-components. In the most extreme case, this correlation equals one for an individual, which means that the two within-components involved are not separable for this very individual. When the data of the latter individual would be analyzed with PCA, the two within-components would end up into one component.

To sum up, when the interest is in considering the inter-individual differences in intra-individual structure, one should examine the differences across individuals in (co)variances of within-components. Whether those differences are possibly present in the model representation, depends on the SCA variant involved. If capturing any possible differences in intra-individual structure is of key importance, the least constrained SCA-P model is to be preferred.

Sources of Inter-Individual Variability in the MLSCA Model

The inter-individual variability is described by the between-loadings and between-component scores. The between-loading matrix expresses which variables covary strongly across individuals, in terms of the average level across measurements. The between-loading matrix has transformational freedom, implying that it can, for instance, be rotated towards simple structure. The between-component scores reflect the relative positions of the individuals on the between-components.

Different Sources of Intra- and Inter-Individual Variability in the MLSCA Model

The between- and within-loading matrices may, and in practice often will, differ from each other. For example, to assess their mood structure across time, 12 individuals diagnosed with Parkinson's disease scored a mood questionnaire on 53–71 consecutive days (Shifren, Hooker, Wood, & Nesselroade, 1997). The questionnaire used was the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988), which measures two dominant dimensions of emotional experience. Each day, the individuals rated the degree to which they experienced specific mood aspects that day. The MLSCA of the resulting scores (see Timmerman, 2006) revealed that the inter-individual differences in within-subject means across the different days could be described by two components, namely Positive and Negative affect. This structure was completely in line with the one reported by Watson et al. (1988). On the contrary, the intra-individual mood structure, which expresses the daily fluctuations about the within-subject means, was described well by two uncorrelated within-components. The latter were labeled as introversion and emotional stability. Those results are in line with findings that positive and negative emotional traits, that is the within-subject means, are independent, but that positive and negative emotional states are negatively related within subjects (Vansteelandt et al., 2005). This contrasts to suggestions that positive and negative affect form the dominant dimensions of both emotional traits and states (Watson & Clark, 1994; Zevon & Tellegen, 1982).

Model Selection, Stability, and Inference

The aim in modeling data using a component model is to separate the observed data into a systematic and a residual part, where the systematic part is described by an interpretable and preferably sparse model that would fit the population data well. The latter means that a model with relatively good fit and low complexity is favored. This idea underlies the well-known scree-test (Cattell, 1966) as well. As a measure of fit, the proportion of variance accounted for (VAF) is usually considered, because it indicates which part of the observed data is covered by the model. In MLSCA, the model complexity is influenced both by the specific variant considered and by the number of components. In practice, a series of MLSCAs is performed, using the different model variants, with various numbers of components. Then, the models are ordered from least to most complex and the model(s) with a relatively large difference in VAF compared with the preceding model and a relatively small difference in VAF compared with the subsequent model are considered. The interpretability should play a key role in the final model selection.

Once a model has been selected for the sample data, one may wish to verify to what extent the model is reasonable for describing the population data as well. As population data is not available, one has to resort to considering the stability of the estimated models over subsamples of the data at hand. A complicating issue is that one deals with multiple populations, namely the population of measurements of each individual observed, and, possibly, the population of individuals from which the sample has been drawn. In practice, one may wish to generalize to only a part of those populations, rather than all populations. Moreover, one may be interested in only parts of the model, like the within-loadings. Then, one should consider the stability for part of the populations, or parts of the model. The stability of model parts can be assessed via split-half analysis, as described in Timmerman (2006).

Apart from the stability of the full model over samples, one may consider inferential information on the individual parameters. Confidence intervals on individual parameters can be estimated using the bootstrap (Timmerman, Kiers, Smilde, Ceulemans, & Stouten, 2009). Herewith, it is important to decide whether only a generalization to the population of measurements within the individuals is warranted, or also to the population of individuals, because this influences the resampling strategy to take. One should realize that small sample sizes yield unreliably estimated confidence intervals (Timmerman et al., 2009), that is, the estimated CIs are consistently too small.

MLSCA or Multi-Group/Multilevel SEM?

The model used in MLSCA shows much resemblance to particular Structural Equation Model (SEM) variants, which are known as multi-group and multilevel SEMs (see e.g., Jöreskog, 1971; Muthén, 1989; Du Toit & Du Toit, 2008). For a discussion of the relationships between MLSCA and multi-group and multilevel SEMs, we refer to Timmerman et al. (2009). The key difference between the approaches used with Component Models (CMs) and SEMs is in the definition of the factors. In CMs the factors (components) are based on the observed variables, and in SEMs on the common parts of the variables. This seemingly minor detail has many consequences, which has been extensively described in comparisons of special cases of the two approaches: PCA and Common Factor Analysis (CFA; e.g., Jolliffe, 2002; Widaman, 2007).

In a CFA the factors are based on those parts of the variables that at least some variables have in common, while the unique parts of the variables are set apart as different factors. In a PCA the factors are based on the observed variables and the distinction between common and unique parts is simply being ignored. Because it is reasonable to assume that each observed variable suffers from measurement error, and thus is partly unrelated to other variables, a CFA is more complete than a PCA. This incompleteness provides the main objection to PCA.

It is well-known that when a Common Factor Model (CFM) holds perfectly, and a PCA is performed, the PCA parameter estimates consistently differ from the population parameters (Widaman, 1993, 2007). Hence, if a CFM holds exactly, a common factor analysis is to be preferred. However, as is now widely recognized, all common factor models in the social sciences are an *approximation* to reality (Browne & Cudeck, 1992). Therefore, it is important to know how close an estimated model is to 'reality', hence what the size is of the so-called model error. Because of their approximating characters, in empirical applications, the model error of an estimated PCA could be similar or even smaller than that of an estimated CFM.

Even if CFM would be superior over PCA in terms of model error, one may question whether a PCA based interpretation essentially differs from a CFM based one. If one only looks for clusters of variables to interpret the factors (components), CFM results will offer the same interpretation (unless unique variances are very high, or highly unequal across the variables associated to the same factor).

Apart from the essential difference in the definition of the factors, there are differences in tradition between CFM and PCA, respectively, like in the typical estimation procedure (maximum likelihood versus least squares), distributional assumptions (strong versus weak) and model approach (confirmatory versus exploratory). Although those properties are by no means intrinsic to either of the methods, they do affect the practical use of the models. For example, when a distributional assumption required for a particular common factor analysis (CFA) is violated, this results in an increase of model error, which reduces the headstart of CFA over PCA. Those differences in tradition become even more influential in more complicated types of analysis, like MLSCA and multi-group SEM. For example, a confirmatory approach requires strong ideas about 'the' correct model, because otherwise the risk of missing this model becomes rather large. The confirmatory nature of SEM analyses is important in the current context: when examining sources of intra-individual variability, strong theoretical guidance is usually lacking, and hence exploratory methods are called for.

A further advantage of the use of a CM over SEM is that component scores are readily obtained, whereas factor scores can only be estimated, with different methods yielding different estimates. Because in the current context both the between- and within-component scores provide information on the individual, it is advantageous to have them directly.

In empirical data analysis, identification and estimation problems trouble SEMs more than component models. That is, sample size limitations, problematic data sizes (e.g., very large number of variables) or severe violations of distributional assumptions may hinder a successful empirical use of SEM, whereas a Component Analysis is much less sensitive to those requirements.

To sum up, the model used in MLSCA is incomplete in that it does not account for unique variances. However, in empirical applications, it is questionable whether the estimated MLSCA model suffers from a larger model error than its counterpart that does account for unique variances. Moreover, because a MLSCA solution can be obtained in nearly all applications, MLSCA may be the only option to arrive at an insightful solution.

Related Models to MLSCA

The key idea of MLSCA is to disentangle the sources of within- and between-variance in the data. This very idea underlies the integrated trait-state model (ITS model; Hamaker, Nesselroade, & Molenaar, 2007) as well. More specifically, an analysis with the ITS model aims at identifying subgroups of individuals with identical within-models. The essential difference between the two models is that MLSCA is a CM and the ITS model a SEM, implying that the latter explicitly models unique variances. As explained in the previous section, CM and SEM differ in tradition. This shows up when comparing MLSCA with the ITS model. For example, the ITS model assumes the within-factor scores to follow an auto-regressive model, which makes the ITS model more restrictive than MLSCA. Furthermore, the ITS model is confirmatory, as is for instance illustrated by the example presented by Hamaker et al., 2007. Finally, in the ITS model, the similarities between subgroups with different within-models are relatively difficult to detect. In MLSCA, those similarities and differences in within-models get ample attention, albeit possibly at the cost of less precision.

When considering related models to MLSCA, the work of Flury (1988) cannot remain unnoticed. Flury discusses a hierarchy of CMs (1988, pp. 60–62) for multi-group data that can be applied equally well to repeatedly gathered data from more than one individual. Flury's models cover the within-part of the data, and bear close resemblance to SCA (see Section "Sources of Intra-Individual Variability in the MLSCA Model"). In fact, the most constrained model of Flury equals SCA-ECP and Flury's Common Principal Component (CPC) Model equals SCA-IND. Flury also discusses the Partial CPC model, which involves both common within-loadings and individual specific loadings. The main difference is the estimation, where Flury uses maximum likelihood and MLSCA least squares optimization.

Empirical Applications of MLSCA

Emotions in Daily Conflicts Between Adolescent Girls and Their Mothers

As a first illustration of the usefulness of MLSCA, we present an empirical example from a study on emotions in daily conflicts between adolescent girls and their mothers. Until now, research on adolescent-parent relationships has primarily focused on the content and frequency of conflicts. The emotions involved in such conflicts remain largely understudied and if affective aspects are included, they are usually reduced to a positive–negative dichotomy. In this study we focus on the emotions *after* conflict. Based on findings from observational research on marital interactions (Gottman & Levenson, 1999) we know that the ability to rebound, implying a neutral or positive feeling after conflict, may be more important to relationship quality than the amount of "negativity" expressed during conflict.

To obtain a proper understanding of the emotional processes associated with conflict interactions, it is essential to examine various conflicts within the girls across time. Therefore, we conducted a diary study in which fifteen 15-year-old girls reported on their daily conflicts with their mothers. The diaries consisted of 6 waves across 1 year and each wave comprised a 2-week diary episode, where the girls were instructed to report on each conflict they had with their mother during this period. Because of the explorative nature of this study the emotions after conflict were assessed with an extensive list of 17 different emotions (see Table 14.1). The girls indicated to what extent they felt certain emotions on a 4 point Likert scale (ranging form 0 = not at all to 3 = very much). The girls completed on average nine weeks of daily diary (calculated in days: Mean (M) = 67, Standard Deviation (SD) = 13.8, *range* = 26–77). In total, scores were obtained on 142 conflicts (M = 9.47; SD = 4.39).

Table 14.1 Varimax rotated between-loadings (left part) and within-loadings (right part) of the emotion-after-conflict data. Loadings greater than ±0.30 are highlighted in bold face

	Between				Within			
	Positive	Negative internal	Frustration	Neutral	Positive	Negative internal	Indignant	Guilt
Hopeful	**0.34**	−0.01	0.02	−0.20	−0.26	−0.09	−0.00	**0.44**
Relieved	**0.48**	0.05	0.12	−0.12	**0.61**	−0.12	−0.07	−0.07
Happy	**0.41**	−0.01	0.09	−0.04	**0.76**	−0.05	−0.05	−0.18
Proud	**0.32**	−0.02	−0.03	−0.06	**0.62**	−0.00	0.01	**0.38**
Disappointed	−0.06	**0.42**	−0.17	−0.09	−0.08	**0.53**	0.21	0.09
Sad	0.14	**0.51**	−0.06	−0.03	−0.11	**0.63**	0.14	−0.10
Lonely	0.02	**0.39**	−0.09	0.04	−0.03	**0.73**	0.07	−0.03
Hurt	−0.09	**0.40**	−0.08	0.05	0.04	**0.75**	−0.02	−0.03
Frustrated	−0.25	−0.08	**0.51**	−0.07	−0.10	−0.10	**0.35**	0.10
Angry	−0.13	0.09	−0.27	−0.03	−0.07	0.12	**0.69**	−0.06
Not taken serious	−0.08	0.15	−0.24	−0.05	−0.05	0.21	**0.63**	−0.18
Misunderstood	−0.18	0.17	−0.29	−0.05	−0.03	0.13	**0.43**	−0.18
Neutral	−0.08	−0.09	−0.03	**0.41**	0.15	−0.10	**−0.48**	0.17
Guilty	0.06	−0.06	−0.04	−0.32	−0.06	0.12	0.01	**0.61**
Regret	0.08	0.00	−0.03	−0.28	0.12	−0.08	−0.07	**0.47**

Based on the work of authors in the field of personality and emotional development (Lewis, 1995, 2000; Magai & McFadden, 1995; Magai & Nusbaum, 1996) we expected to find differences between the girls in their "dominant" emotional pattern, i.e., their general level of emotions after conflict. Based on theories within the field of social (e.g., Frijda, 1986, 2001; Lerner & Keltner, 2000; Roseman & Evdokas, 2004) as well as clinical psychology (e.g., Guerrero & La Valley, 2006; Sanford, 2007) we expected that those differences in dominant patterns between the girls could best be described along four emotional dimensions, namely internal negative emotions, anger related emotions, guilt related emotions, and positive emotions.

Due to the lack of knowledge about the individual patterning of emotions over time we did not have any predefined hypotheses with respect to the intra-individual emotional structure. On the basis of theories about personality development (Lewis, 1995, 2000; Magai & McFadden, 1995; Magai & Nusbaum, 1996), which state that emotional development is a highly idiosyncratic process, we did expect to find inter-individual differences in the organization of emotions over time. Therefore, we wished to explore how emotions organize within the girls over time, to what extent this differs across girls, and how this relates to the girls' dominant emotional patterns over time. In addition, based on our own empirical work and the work of others (Granic, Hollenstein, Dishion, & Patterson, 2003) we expected to find inter-individual differences in the intra-individual variability of the emotions over conflict episodes, i.e., that the girls would differ in the degree to which they vary in their emotions over time.

In order to explore the above mentioned hypotheses and questions we applied MLSCA analyses to the 142 conflicts by 17 emotions data matrix. Because we wished to express possible differences in intra-individual structure across girls as good as possible, we preferred the—least constrained—MLSCA-P model. The between- and within-scree plots did not provide a clear indication on the numbers of components. On the basis of the interpretability a MLSCA-P solution with four between-components and four within-components was chosen.

The within-variance made up the largest part of the total variance (77.72%) and the between-variance the remaining 22.28%. This implies that there is more variation within the girls over conflict episodes than between the girls on the average level. With the MLSCA-P model, the four between-components accounted for 77.66% of the between-variance (which is 17.31% of the total), and the four within-components accounted for 51.22% of the within-variance (which is 39.80% of the total). As can be seen in Table 14.2, the percentage of within-variance accounted for (VAF) per girl ranged from 25.96 to 81.42% (M=45.55%, SD=15.85%). Although the VAF per girl was generally satisfying there were also some girls whose data were not described by the model very well.

The between-part of the selected MLSCA-P solution gives insight into the inter-individual emotional structure in dominant emotional patterns over time. The four Varimax rotated between-loadings (see left part of Table 14.1) were interpreted as *Positive*, *Negative Internal*, *Frustration*, and *Neutral*. This partly supported our hypotheses concerning the between-structure of the emotions. As expected, the positive emotions and negative internal emotions formed separate clusters. We had

Table 14.2 The left part presents the variance accounted for (VAF) per girl. The middle part displays the between-component scores for the individual girls; component scores greater than 1 are highlighted in bold face. The right part of the table gives the within-component variances, which are computed across all conflicts of a girl; variances greater than 1 are highlighted in bold face.

Girl	VAF	Between-component scores				Within component variances			
		Positive	Negative internal	Frustration	Neutral	Positive	Negative internal	Indignant	Guilt
1	62.32	−0.71	0.43	−1.10	−0.59	0.05	**3.19**	**1.48**	**1.25**
2	30.90	0.30	−0.61	−0.21	0.96	0.62	0.01	0.56	0.03
3	42.76	−0.12	−0.76	0.03	**1.84**	0.04	0.04	**1.18**	0.11
4	46.09	**1.46**	0.71	−0.23	−0.20	**3.13**	0.96	0.90	1.41
5	52.73	**1.35**	−0.20	−0.20	−2.49	**1.54**	0.64	0.17	**9.43**
6	27.47	−0.36	0.18	−0.82	−0.18	0.13	0.79	0.45	0.74
7	81.42	0.03	**3.67**	−0.06	0.74	0.46	**8.65**	**3.70**	0.09
8	42.19	−0.78	0.13	−0.09	0.08	0.14	0.53	**2.46**	0.07
9	44.00	−0.43	−0.64	−1.71	−0.98	**1.35**	0.11	**1.55**	**1.47**
10	32.71	−0.20	−0.74	−0.45	0.50	0.03	0.01	0.37	0.13
11	64.12	**2.87**	−0.60	0.20	0.77	**7.40**	0.04	0.13	**1.62**
12	31.43	0.37	−0.31	1.58	−1.66	**2.15**	0.08	0.31	**1.61**
13	39.26	−0.89	−0.58	−0.31	−0.40	0.02	0.16	**1.69**	0.57
14	59.82	**2.30**	0.18	0.51	0.40	**5.31**	0.30	0.06	0.52
15	25.96	−0.96	−0.07	**1.98**	−0.19	0.17	0.04	0.28	0.10

predicted separate clusters of guilt related and anger related emotions, which both hardly showed up. Instead of guilt related and anger related emotions, the important emotions to express differences in girls in dominant emotions across time appeared to be frustration for the third component, and the neutral emotional category for the fourth component. The latter could have been labeled also as a rebound component. That is, feeling neutral means that they have recovered from the negative emotions experienced during conflict.

Subsequently, we investigated the girls' scores on the four distinguished dimensions in dominant emotional reactions, i.e., the between-component scores (see middle part of Table 14.2). Between-component scores are standardized over girls and conflicts (i.e., scaled to have a mean of zero and variance of one across girls' conflicts and weighted according to their number of conflicts). Therefore, a between-component score indicates to what extent this girl scores above (or below) average, on this very component.

We first inspected per component the distributions of the between-component scores (see middle part of Table 14.2). The between-component Positive appeared to be rather right-skewed, with a few girls scoring high, whereas Frustration and Neutral are more symmetrically distributed. The component Negative internal appeared rather symmetrically distributed, with one clear positive outlier (Girl 7). When considering the pattern of between-component scores per girl, five girls appeared to score close to the mean on all four between-component scores (i.e., within one standard deviation). The remaining girls scored high (larger than one standard deviation from the mean) on at most two between-components. These emotional profiles can be used for additional analyses, like studying the relationship between a predominantly negative internal reaction to conflicts and the autonomy development of the adolescent girl. A possible hypothesis is that forming a pattern of negative internal emotions to conflicts could bear the risk of withdrawing from conflicts and giving up the fight for autonomy. The within-part of the selected MLSCA-P solution offers insight into the variability of emotions within the girls over conflict episodes. That is, it provides information about the intra-individual structure and the intra-individual variability of emotions over time.

Based on the Varimax rotated within-loadings, the four within-components were labeled as Positive, Negative internal, Indignant, and Guilt (see right part of Table 14.1). We did not have any predefined hypotheses concerning the structuring of emotions within the girls over time. Inspection of Table 14.1 reveals several interesting differences and similarities in the between- and within-parts of the model.

First of all, it is interesting to note that the within-loadings were considerably higher than the between-loadings. This implies that the within-part of the model explains a larger proportion of the total variance than the between-part. This is completely in line with the fact that the within-variance was 77.72% of the total variance. For example, the within-loadings of anger are much higher than the between-loadings. The variance at the within-level makes up 84% of the total variance of anger. This means that girls do vary relatively much in their anger scores over conflict episodes, but not so much in their general level of anger, which is probably due to the fact that anger is a common emotion after conflict.

Secondly, comparing the between- and within-components revealed a salient similarity in the first two components, with almost the same clusters of emotions showing high loadings. Therefore, the same names were attached to those two components, namely Positive and Negative internal. However, the loadings on the other two between- and within-components revealed interesting differences.

The third within-component, which we have labeled Indignant, is characterized by high loadings for anger, frustration, the feeling of not taken serious and misunderstood, and not feeling neutral. This cluster of emotions can be interpreted as a typical teenage-component, i.e., feeling indignant after conflict, probably due to the fact that they didn't succeed in gaining the wanted autonomy. Thus, we found the expected cluster of anger-related emotions at the intra-individual level, which is in contrast to our findings at the inter-individual level.

The fourth within-component that we labeled Guilt is characterized by high loadings for guilt and regret. Additionally, the emotions of hope and proud had considerably high loadings on this within-component. That hope went together with feelings of guilt and regret over conflict episodes can be explained by an attempt to repair.

Inter-Individual Differences in Intra-Individual Structure

Inter-individual differences in intra-individual structure find expression in the variances of and correlations between the within-components, as explained in Section "Sources of Intra-individual Variability in the MLSCA Model". To assess inter-individual differences in the girl's emotional structure across conflict episodes, we inspected the variances of and correlations between the four within-components.

As can be seen in the right part of Table 14.2, the individual variances differed considerably across girls per within-component, implying large inter-individual differences in terms of variability of emotions over conflict episodes. Moreover, the girls' relative degrees of variability differed across within-components. For instance, Girl 11 had the highest amount of variability on the Positive component, and Girl 7 on the Negative internal component. On the other hand, there are some girls, like Girls 2, 10, and 15, who showed little variation across all four within-components. A low within-component variance means that that this within-component is of hardly any relevance for the girl involved. For instance, Girl 2 almost never reported emotions associated to the Guilt and Negative internal emotion components; hence she had almost zero variation on these two components. Consequently, her emotional structure over the conflict episodes could have been best described by means of two components (i.e., Positive and Indignant).

The individual correlations between the within-components that appeared higher than 0.75 in absolute value are displayed in Table 14.3. Note that for girls with small numbers of reported conflicts, the correlation pattern should be read with caution. As can be seen in Table 14.3, several girls showed rather high correlations between particular within-components, implying that for those girls the components involved could be combined. Girl 3 is an interesting case because she showed correlations between all four within-components larger than 0.75 (except for Positive and Negative internal that still correlated 0.49). Thus, the reported emotions of Girl 3 across conflict episodes could be described to a rather large extent using only a single component.

In sum, investigating the individual correlations of the within-components and the variances of the within-components revealed interesting additional information about differences between the girls in the way their emotions are organized across

Table 14.3 The individual correlations between the within-component scores. Only correlations above ±0.75 are reported here

Girl	# Conflicts	Within-component pair		Correlation
2	7	Negative internal	Indignant	−0.96
3	13	Negative internal	Indignant	−0.91
3	13	Negative internal	Guilt	0.83
3	13	Positive	Indignant	−0.77
3	13	Positive	Guilt	0.84
3	13	Indignant	Guilt	−0.88
7	8	Negative internal	Guilt	−0.83
9	8	Negative internal	Indignant	−0.78
11	5	Negative internal	Positive	−0.86
11	5	Indignant	Guilt	−0.77
14	7	Indignant	Guilt	−0.93
15	15	Indignant	Guilt	−0.90

measurement points. Based on the idiosyncratic nature of emotional development we expected to find differences in the intra-individual structure of emotions. The MLSCA-P model allowed us to explore these differences while at the same time also pointing out the similarities between the girls.

The Course of Emotions over Conflict Episodes

To assess the course of emotions across conflict episodes, we plotted, for each girl, the within-component scores against time. Two exemplary plots are presented in Fig. 14.1. For Girl 7, the 5th and 6th conflict were predominantly characterized by high levels of positive emotions. After conflicts 7 and 8, she reported high levels of negative internal emotions. It would be interesting to relate these time plots to additional information about the conflicts, to assess whether any relationship exists between the topic, the solution of the conflicts and the reported emotions. For example, it might be that Girl 7 "won" the 5th and 6th conflict, and therefore felt happy afterwards. In addition, the time-plots can also be used to analyze trends in the emotional organization over time.

While visually comparing the graphs across the 15 girls, a salient difference between two groups of girls emerged, namely those who tended to fluctuate much in their emotions across conflicts, and those who were very stable across time. We denoted those groups as the *flexible* and *rigid* girls, of which Girls 7 and 10 are respective examples. Observational research has shown the negative consequences of emotional rigidity within conflict interactions in terms of the development of the adolescent and the parent-child relationship (Granic et al., 2003). It would be interesting to investigate whether the same effects can be found for emotional rigidity across conflict interactions.

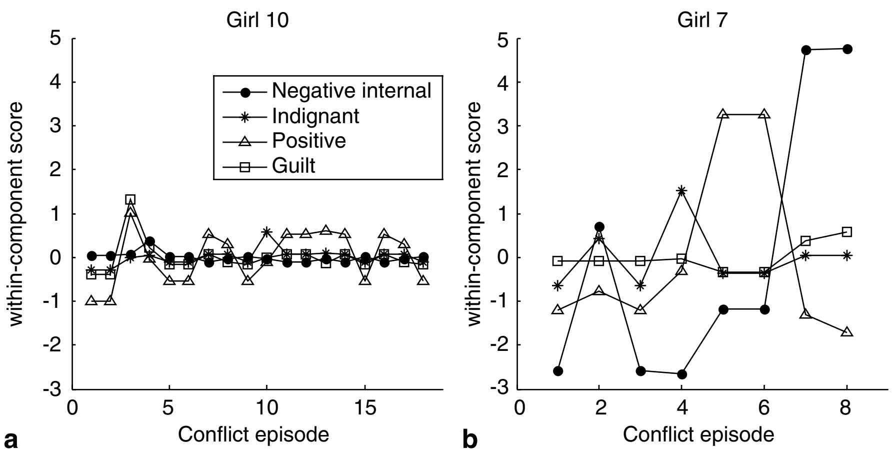

Fig. 14.1 Within-component scores plotted against conflict episodes for (a) Girl 10 and (b) Girl 7

Relating Differences in Dominant Emotional Pattern to Intra-Individual Variability

As we have outlined above, the first and second between- and within-components were characterized by the same clusters of emotions. For those components, it is interesting to relate the between-component scores, i.e., the dominant emotional pattern, to the individual within-component variances, the intra-individual variability over conflict episodes (see Table 14.2). In both cases, a strong positive relationship emerged: for the Positive and the Negative internal components we found correlations of 0.92 and 0.95, respectively (and even without the outlier (Girl 7) the correlation for Negative internal is still 0.65). In sum, the high correlations imply that the higher the score on the general level of Positive and Negative internal emotions, the more they fluctuate in these emotions over time. This suggests that girls who showed a low variability on these two within-components did in fact (almost) always score zero on these emotions.

The analyses presented here revealed interesting differences with regard to the inter- and intra-individual structuring of emotions. We have shown that it is important to go beyond a positive–negative dichotomy and to distinguish between several distinct positive and negative emotions. This holds for the inter-individual as well as the intra-individual emotional structure. In both cases negative internal emotions came out as a separate emotional component. Several interesting hypotheses can be further tested on the basis of the dominant emotional reactions. The work of Strayer (2002) provides several hypotheses concerning the link between emotional profiles and the identity development of adolescents. For instance, too few anger and too much negative internal emotions could lead to impaired levels of autonomy and therefore undermines the development of a self-defined identity. In this way one can explore the link between emotional processes as expressed in the diaries and relational aspects or adolescent developmental outcomes, as measured in for instance questionnaires.

Furthermore, we also have found interesting results with regard to the intra-individual structure of emotions. The variances and correlations revealed information about the “use” of certain emotional components as well as the variability over time. In that way the girls can be distinguished on the basis of the size of their emotional repertoire (i.e., how much components do they use) and their emotional variability (i.e., flexible versus rigid girls). Also this information can then be used for further analyses. In the literature, several negative consequences of emotional rigidity have been reported, such as negative effects on the relationship and developmental outcomes (Granic et al., 2003; Hollenstein, Granic, Stoolmiller, & Snyder, 2004). A rich, complex, and balanced emotional profile on the other hand corresponds to higher personality, ego, self, and identity development (Abe & Izard, 1999; Magai & McFadden, 1995; Strayer, 2002).

Drive for Thinness, Affect Regulation, and Physical Activity in Eating Disorders

As a second illustration of the usefulness of MLSCA, we present an empirical example from eating disorder research. It has been observed that a substantial proportion of patients with eating disorders, like anorexia nervosa or bulimia nervosa, engage in high levels of physical activity (Beumont, Arthur, Russell, & Touyz, 1994; Davis, 1997; Solenberger, 2001). To explain this observation, one often recurs to underlying psychological processes, like drive for thinness on the one hand and affect regulation on the other hand. The drive for thinness hypothesis states that eating disorder patients attach great value to weight and are actively trying to modify their body shape; physical activity and the resulting burning of calories is then just one of the ways to obtain the desired thinness ideal (Davis, 1997; Davis, Kennedy, Ravelski, & Dionne, 1994; Heatherton & Baumeister, 1991). The affect regulation hypothesis reads that physical activity is a way of coping with chronically negative affect (Davis, Katzman, & Kirsh, 1999; Holtkamp, Hebebrand, & Herpertz-Dahlmann, 2004; Thome & Espelage, 2004). To obtain an understanding of the psychological processes involved in excessive physical activity in eating disorder patients, it is important to consider these psychological processes both at the between and the within patients level. After all, the above cited findings that drive for thinness and affect regulation are related to physical activity at the between patients level, do not necessarily imply that this is also the case at the within patients level. As such, investigating whether these between patients relations between these three phenomena also show up at the within patients level, is important for the development of effective therapeutic treatments.

To study the relations between drive for thinness, affect regulation, and physical activity in eating disorders between patients and within patients across time, Vansteelandt, Rijmen, Pieters, Probst, and Vanderlinden (2007) conducted a study that included 32 female inpatients of the specialized inpatient eating disorders unit of the University Psychiatric Center in Leuven, Belgium. Nineteen of these participants suffered from anorexia nervosa and 13 from bulimia nervosa. During 1 week, these 32 patients filled out a questionnaire at nine randomly selected times a day. The patients were signaled to do so by an electronic device. The questionnaire consisted of 22 items that aimed at measuring the different processes under study. In particular, to measure affect regulation the patients rated the presence of 12 positive and negative emotions. The patients' momentary drive for thinness was tapped by means of four slightly adapted items from the Dutch version of the Eating Disorder Inventory (EDI; Garner, 1991; Van Strien, 2002). The urge to be physically active and physical activity itself were measured by three items. All 22 items were rated on a 7 point Likert-scale (ranging from 0 = not applicable at all to 6 = completely applicable). Sometimes the patients were not able to report. In total, scores were obtained on 1459 measurement occasions, implying that there are 557 missing measurement occasions. Whereas the mean numbers of obtained measurement occasions varies considerably across the patients (M = 45.59 per patient; SD = 10.95), they vary relatively little across the days of the week (M = 208.43 per day of the week; SD = 9.48).

A major advantage of this study over previous studies regarding physical activity, is that its design allows to simultaneously investigate both the between- and within-patient relations between affect, drive for thinness, and physical activity. At the between-patients level, we expected to find 4D namely physical activity, chronically negative affect, chronically positive affect, and dispositional drive for thinness. Furthermore, we expected to find substantial relationships between physical activity, chronically negative affect, and dispositional drive for thinness. Within patients, momentary drive for thinness and emotional states were expected to covary with physical activity over time. Furthermore, we wished to examine whether differences exist *across* patients in the *within*-patient variances of drive for thinness, emotional states, and physical activity, and in the within-patient relations between these three phenomena. For example, within-patient variances and within-patient relations between drive for thinness, affective states and physical activity may be especially strong in patients with more pronounced eating disorder pathology as indicated by, for example, a lower body mass index and more severe depression.

In the 1459 signals by 22 item data matrix, the between-variance made up 51.69% of the total variance and the within-variance the remaining 48.31%. This implies that affect, drive for thinness, and (urge for) physical activity vary substantially between patients as well as within patients. To gain insight into the between- and within-patient covariation of these processes, MLSCA analyses with 1 up to 6 between- and within-components were applied to the data.

The Between-Part

On the basis of the between-scree plot in Fig. 14.2a and interpretability, the between-solution with 4 components was selected. This solution accounts for 84.6% of the between-variance in the 22 measured items, corresponding to 43.7% of the total variance in the data.

In an attempt to achieve simple structure, the between-loadings were first Varimax (Kaiser, 1958) rotated. As the resulting loadings still showed strong cross-

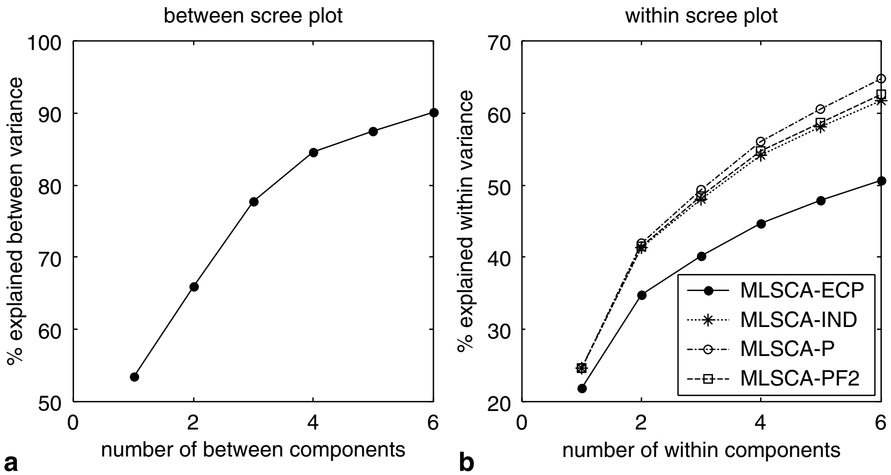

Fig. 14.2 Percentage of (a) explained between-variance for MLSCA solutions with the number of between-components varying from 1 to 6, and (b) explained within-variance for MLSCA-ECP, MLSCA-IND, MLSCA-PF2, and MLSCA-P solutions with the number of within-components varying from 1 to 6

Table 14.4 Promax rotated between-loadings (left part) and within-loadings (right part) of the eating-disorder data. Loadings greater than ±0.30 are highlighted in bold face. PA vs NA is Positive versus Negative affect

	Between				Within	
	Negative affect	Positive affect	Urge to be physically active	Drive for thinness	PA vs NA	Physical activity
Pleased	−0.07	0.45	0.03	−0.05	0.61	0.04
Happy	−0.08	0.59	0.01	−0.02	0.56	0.02
Love	0.11	0.55	0.04	−0.09	0.36	0.06
Appreciated	0.13	0.65	−0.17	0.09	0.35	0.03
Sad	0.56	0.03	−0.08	0.07	−0.59	0.00
Angry	0.51	0.01	0.01	0.01	−0.58	0.07
Lonely	0.53	−0.09	−0.01	0.08	−0.41	0.01
Ashamed	0.70	0.06	0.01	0.07	−0.26	0.02
Anxious	0.79	0.09	0.14	−0.23	−0.33	0.06
Tense	0.65	−0.08	0.18	−0.16	−0.44	0.07
Guilty	0.64	0.02	0.03	0.14	−0.32	0.03
Irritated	0.36	0.07	−0.08	0.31	−0.42	0.06
Want to move	0.11	−0.03	0.75	−0.03	−0.03	0.34
Want to sport	0.12	−0.02	0.71	−0.05	−0.05	0.37
Want to be active	0.11	−0.05	0.77	−0.07	−0.02	0.33
Am active	−0.12	0.01	0.43	0.02	0.13	0.67
Am moving	−0.08	0.06	0.36	0.16	0.10	0.70
Am sporting	−0.06	0.12	0.39	0.10	0.10	0.65
Want to burn calories	0.04	−0.06	0.44	0.45	−0.08	0.21
Feel fat	0.00	0.00	−0.04	0.83	−0.20	0.08
Feel ugly	0.17	−0.05	0.05	0.69	−0.20	0.07
Want to loose weight	−0.07	0.04	0.10	0.78	−0.15	0.10

loadings, an oblique Promax rotation was conducted. On the basis of the resulting between-loadings (see left part of Table 14.4) the between-components were labeled as Negative affect, Positive affect, Urge to be physically active, and Drive for thinness.

To further interpret the between-loadings we considered the intercorrelations among the four between-components. It is interesting to note that Positive affect is unrelated to Negative affect at the between-patients level; this finding is in line with earlier results, for instance of Vansteelandt et al. (2005). Furthermore, as expected, we find that patients with a higher Urge to be physically active are characterized by chronically Negative affect (affect regulation hypothesis) and a stronger dispositional Drive for thinness (drive for thinness hypothesis). These findings may reflect the severity of the eating disorder: patients with more severe eating disorder pathology are characterized by higher levels of Physical activity, more chronically Negative affect and higher dispositions for Drive for thinness. To examine

Table 14.5 Intercorrelations of the four between-components, and with Body Mass Index (BMI), depression measured by the Beck Depression Inventory (BDI), and the symptom severity index (SCL-90)

	Negative affect	Positive affect	Urge to be physically active	Drive for thinness
Positive affect	−0.10			
Urge to be physically active	0.38*	0.05		
Drive for thinness	0.53*	−0.25	0.47*	
BMI	−0.07	0.00	−0.57*	−0.06
BDI	0.48*	−0.43*	0.37*	0.67*
SCL-90	0.44*	−0.46*	0.55*	0.64*

* $P < 0.05$

this hypothesis, we correlated the scores of the patients on the between-components with three indicators of severity of eating disorder pathology: Body Mass Index (BMI), depression measured by the Beck Depression Inventory (BDI), and symptom distress measured by the Global Severity Index of the Dutch adaptation of the Symptom Checklist (SCL-90; Arrindell & Ettema, 1986). These correlations (see Table 14.5) showed that the patients with more severe depression scores, and stronger pathological symptoms are characterized indeed by less chronically Positive affect, and more chronically Negative affect, stronger Urge to be physically active and stronger Drive for thinness. A lower BMI appeared to be associated only to higher Urge to be physically active.

The Within-Part

The within-scree plot in Fig. 14.2b shows that MLSCA-IND, MLSCA-PF2, and MLSCA-P solutions describe the within-part of the data about equally well (see Fig. 14.2b), whereas the MLSCA-ECP solutions are clearly worse. This suggests the use of an MLSCA-IND solution, as for a specific number of within-component such a solution is more restrictive than MLSCA-PF2 and MLSCA-P solutions. Based on the within-scree plot we retained a MLSCA-IND solution with two within-components. This solution accounts for 41.4% of the within-variance, corresponding to 20.0% of the total variance in the data.

The selection of a MLSCA-IND solution implies that the mutual relationships between the processes under study hardly differ across the patients. However, there seem to be considerable differences across patients in the extent to which their affects, drive for thinness and physical activity vary across the different measurement occasions. Before we discuss these differences in more detail, we will first address the interpretation of the two within-components.

The loadings of the 22 items on the two within-components are presented in the right part of Table 14.4. It can be concluded from Table 14.4 that the first within-component can be labeled Positive versus Negative affect. This single bipolar component in the within-structure is in line with previous findings that positive and negative emotional states are negatively related within subjects (Vansteelandt et al., 2005).

The second within-component is clearly characterized by high loadings for the items that measure the actual physical activity; we label this within-component Physical activity. Here it is interesting to note that, in contrast to the between-loadings, the items that measure the Urge to be physically active have smaller within-loadings than the items that measure Physical activity itself. This implies that the largest source of the total variance of actual Physical activity is at the within-level, whereas, for Urge to be physically active, the largest source of the total variance is at the between-level. To interpret this difference in the between- and within-loadings, one first has to take into account that only a proportion of patients with an eating disorder display high levels of physical activity. Thus, only part of the patients have a strong desire to be physically active, implying a large amount of between patient variance in the urge to be physically active. Second, one has to consider that all patients were allowed to go home during the weekend; then, they were more able to engage in excessive physical activity, because on week days physical activity was partly restricted by the therapeutic program. This may explain why for actual physical activity, the largest source of variance is at the within-patient level.

To investigate whether this week/weekend difference in the therapeutic program indeed influenced degrees of Positive versus Negative affect and Physical activity, we considered the difference in means in within-component scores between week days and weekend days. Across all patients, those differences reveal that patients feel more positive during weekends (95% Confidence Interval (CI) [0.36; 0.57]) and report higher levels of physical activity (95% CI [0.06; 0.29]). More importantly, inspecting those differences in means for each patient separately, we found that, during the weekend, 15 of the 32 patients feel more positive and 8 patients engage more in physical activity. To visualize this week/weekend difference, we plotted the within-component scores of patient 28 on the Affect component (see Fig. 14.3a) against time and of patient 2 on the Physical activity component (see Fig. 14.3b), where week and weekend observations are indicated by circles and black dots, respectively.

Inter-Individual Differences in Intra-Individual Variances

As stated before, the selection of the MLSCA-IND solution implies that the covariances of the within-component scores are equal to zero for all the patients. Given the interpretation of the within-components as Positive-versus-Negative-affect and Physical activity, this means that the affect regulation hypothesis did not appear to hold within patients. Furthermore, as the within-loadings of the drive for thinness items are close to zero, the MLSCA analysis reveals no clear evidence in favor of the drive for thinness hypothesis either. As such, within patients, it is not clear which psychological processes cause high levels of physical activity.

With respect to the within-patient variances, retaining a MLSCA-IND solution implies that for some patients the affective state fluctuates more than for others and that some patients show more variation in physical activity than others. Fig. 14.4

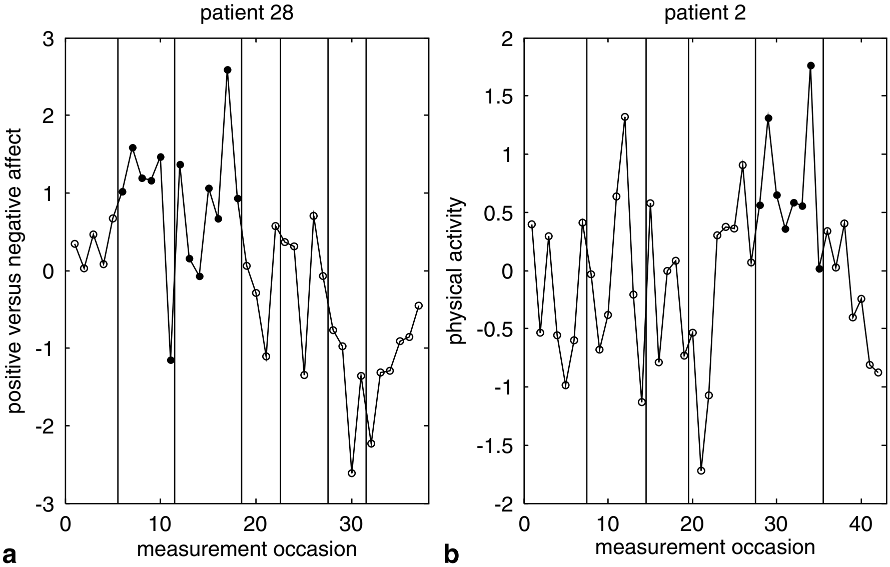

Fig. 14.3 Within-component scores plotted against measurement occasions, for patients 28 and 2. The black dots indicate the weekend observations, the circles denote the week observations, and the vertical lines distinguish the subsequent days

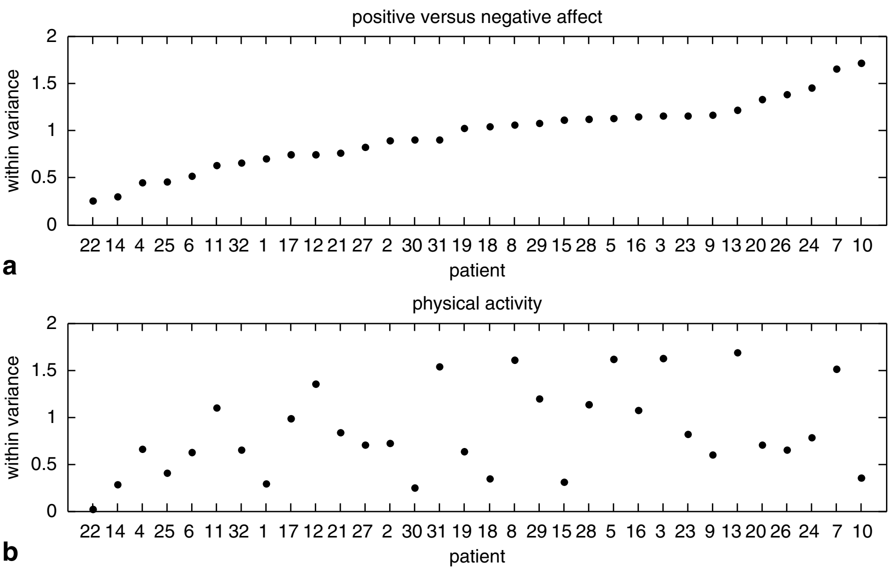

Fig. 14.4 Variances of the within-component scores on (a) Positive-versus-negative-affect and (b) Physical activity, for all 32 patients

visualizes these differences in within-variances. For instance, whereas patient 7 varies a lot in both affect and Physical activity, patients 14 and 22 are very stable across measurement occasions. To interpret these differences across patients in within-variances, we related them to the patients' between-component scores. This revealed that patients with stronger general tendencies to feel negative show larger variability in Affectacross measurement occasions ($r = 0.37$, $p < 0.05$). As a result, patients with chronically negative affect appear to be emotionally unstable. Furthermore, the more a patient's Physical activity varies across time, the stronger her general Urge to be physically active ($r = 0.69$, $p < 0.001$) and her general Drive for thinness ($r = 0.39$, $p < 0.05$). Patients with strong Urges for physical activity may use every opportunity to escape from the restrictions imposed by the therapeutic program on physical activity, whereas patients without such a desire do not try to do this and therefore show less variability in Physical activity.

Summarizing, MLSCA reveals some interesting insights in physical activity in eating disorders at both the between- and within-patient level. At the between-patient level, results indicate that there are substantial differences between patients in the urge to be physically active which are moderately related to chronically negative affect and dispositional drive for thinness, but not to positive affect. In line with previous research (Vansteelandt et al., 2005), positive and negative affect proved to be unrelated at the between-patient level.

At the within-patient level, momentary emotional states and drive for thinness were not related to momentary physical activity. Furthermore, it was found that positive and negative emotional states were negatively correlated. This finding once again (e.g., Vansteelandt et al., 2005) demonstrates that between-subject relations between variables may be independent of within-subject relations between the same variables. Within-patient variability in affect and physical activity was related to week/weekend differences in the therapeutic program regarding for instance restrictions imposed on activity.

Finally, between-patient differences in within-patient variability were detected. Specifically, differences across patients in chronically Negative affect were related to the patient's degree of emotional instability over time. Additionally, differences between patients in dispositional Drive for thinness and Urge to be physically active were related to stronger within-patient variability in Physical activity.

General Conclusion

In this chapter MLSCA is described as a method to identify sources of intra-individual and inter-individual variability in multivariate data which are repeatedly gathered from more than one individual. MLSCA provides component models for the between- and within-parts of the data, to describe the inter-individual and intra-individual variabilities, respectively. To gain a clear understanding of the intra-individual variabilities, it is important to properly express their similarities and differences across individuals. In the MLSCA model, this is regulated via constraints on the covariances and variances of the within-component scores. The two empirical examples illustrated the insights MLSCA may offer. The illustrations showed that individual idiosyncracies may show up in different respects, like relationships between phenomena across time, development across time, or extremely high intensities compared to other individuals. To obtain a complete understanding of human behavior, it is essential to detect and explain those idiosyncracies.

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