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Interindividual differences in intraindividual change in categorical variables

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Abstract

In this article, we proceed from the assumption that constancy and change in development are not necessarily universal. This deviation from the general assumption of universal developmental patterns is embedded in the theory of person-oriented research. In addition, we propose that constancy and change can reflect local associations instead of associations that cover the entire range of admissible scores. Models of Configural Frequency Analysis are proposed to explore and test hypotheses concerning person-specific local associations in repeated observation data. Three models are considered for lagged data. These models differ in the reasons that are assumed as causes for local associations. The first model reflects variable associations of any kind. The second model reflects case-specific variable associations. The third reflects differences between cases. In an example, data from a study on the development of alcoholics are used. The data in this example reflect case-specific associations in the development of drinking behavior over a span of two years. In the discussion, the person- and the variable-oriented elements of longitudinal research are addressed. In addition, assumptions concerning the independence of longitudinal data are made explicit.

Key words: Configural Frequency Analysis, intraindividual change, interindividual change, lagged data, person-oriented research

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Interindividual differences in intraindividual change in categorical variables

Developmental change processes and patterns of developmental change are not universal. Individuals differ in all characteristics of change, for example, timing, speed, duration of change process, amount of change, or qualitative characteristics of change. In standard statistical analysis, researchers often proceed from the assumption that change is universal and that differences from average change reflect measurement error or imperfections of a model.

In this article, we operate under just the opposite assumption. We propose that individuals do differ in change characteristics. Individuals can be grouped together only if these differences are no greater than random. We propose a new statistical method for the analysis of interindividual differences in intraindividual, developmental change. The new method is a variant of Configural Frequency Analysis (CFA; Lienert & Krauth, 1975; von Eye & Gutiérrez-Peña, 2004; von Eye, Mair, & Mun, 2010).

This article is structured as follows. First, we establish the background of this work in the contexts of person-oriented research and CFA. We then present the new approach to comparing individuals in their change patterns. Third, we present an empirical data example from research on alcohol use disorders. Finally, we discuss the present approach in substantive and statistical contexts.

Before we delve into the theoretical and the technical elements of the method to be presented here, however, we briefly illustrate the meaning of the expression "interindividual differences in intraindividual change" (Baltes, Reese, & Nesselroade, 1977). We present two examples. The first illustrates lack of change, on average. In this example, seven artificial trajectories are depicted. Each case is observed on three occasions. The cases start from different levels of behavior. From Time 1 to Time 2, there is no change. Every case stays where they are. In contrast, from T2 to T3, six of the seven cases change, only the case whose trajectory begins with the value of 6 stays unchanged. On average, the sample shows the scale value of 6 for each of the three observation points. However, only one out of 7, that is, 14.3%, shows consistently the same score over the entire observation period. This is depicted in Figure 1. The bold line indicates the average trajectory in the data.

From this example, we draw two conclusions. First, average values often fail to describe the activity in a population. For example, using data from a study on the development of alcohol use disorders, von Eye and Bergman (2003) showed that autocorrelations of averaged scores may fail to describe any single individual in a population. The second conclusion we draw is that differences in development, that is, interindividual differences in intraindividual constancy and change may disappear when change is described based on averaged scores. Both of these conclusions are key to the person-oriented research perspective outlined in the following section.

The second example also uses artificial data. It describes six cases, also observed over three points in time. Each of these cases displays change. Three of the six cases show a change in the linear trend such that an increase from T1 to T2 is followed be a decrease from T2 to

T3. The other three cases show an increase from T1 to T2 and an accelerated increase from T2 to T3. This is depicted in Figure 2. The bold line indicates the averaged increase.

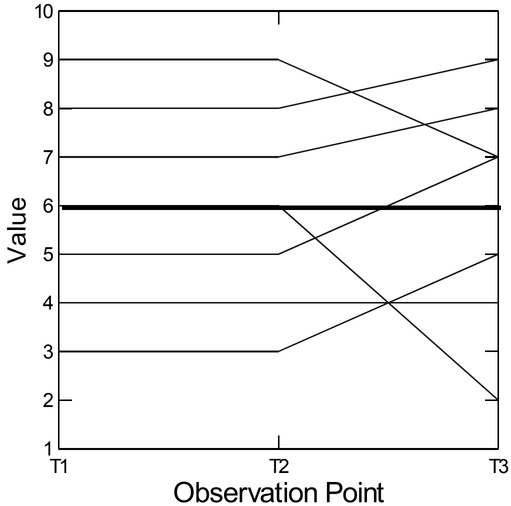

Figure 1:
Interindividual differences in intraindividual change when there is, on average, constancy

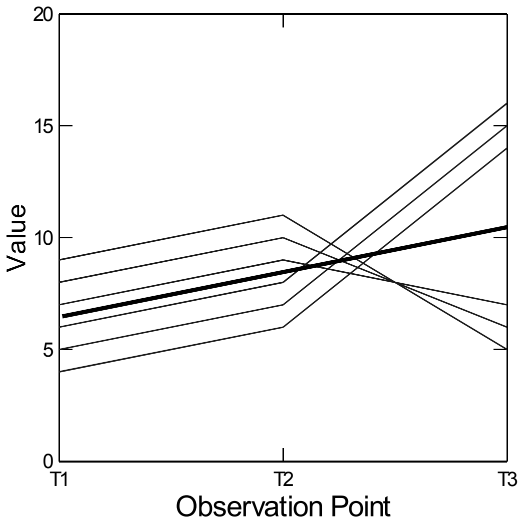

Figure 2:
Interindividual differences in intraindividual change when there is, on average, a linear trend

Figure 2 illustrates again that the average trajectory can fail to describe any of the cases in the sample. Whereas the average trajectory suggests a consistent linear trend over the three observation points, each of the cases shows a break in linear trend. The conclusion from this example is that the stability in development that is suggested by the unchanged average linear trend misses the developmental activity simulated in these data. The conclusions from both examples are captured by the tenets of person-oriented research. Two of these tenets are discussed in the next section.

Person-oriented developmental research

Person-oriented research was introduced by Bergman and Magnusson (1997; cf. von Eye & Bergman, 2003; Bergman, von Eye, & Magnusson, 2006; von Eye, Bergman, & Hsieh, 2013). Interwoven with holistic research, the main tenets that are of interest for the present work are

1. Functioning, process, and development of behavior are, at least in part, specific and unique to the individual; and
2. developmental processes occur in a lawful way and can be described as *patterns* of the involved factors; development can be described by constancy and change in these patterns; the meaning of the involved factors is determined by the factors' interactions with other factors.

Other tenets concern the holistic nature of development, the number of factors that need to be taken into consideration, the number of meaningfully different patterns, and the conditions that must be fulfilled for meaningful comparisons (see von Eye & Bergman, 2003; von Eye, 2010).

The first of the two tenets considered here proposes that, in principle, each individual can exhibit developmental characteristics that are unique and make the individual different from all other individuals. This does not imply that, as was illustrated in the examples in Figures 1 and 2, every individual differs from all other individuals in all respects. Similarly, this does not imply that every individual necessarily differs from all others in one or more aspects. However, differences can exist and they can be meaningful. Therefore, we intend to take them seriously, and we assign individuals to the same group only when we can be sure that they are homogeneous within the group.

The second of these tenets is related to Bergman and Magnusson's (1997) holistic perspective. It proposes that change is multifaceted and multidimensional, and that all facets and dimensions need to be taken into account. In other words, it is not sufficient to describe change in just one variable. Change (or lack of change) in multiple variables needs to be described simultaneously. Change in multiple variables constitutes *patterns of change*, and these patterns, once established, are the unit of analysis (cf. Bergman, Nurmi, & von Eye, 2012). Patterns can be described by lists of categories in categorical variables or, as was illustrated in the examples in Figures 1 and 2, by trend parameters that represent a trajectory. Interindividual differences in intraindividual change are reflected in different categories or in differences in trend parameters. In the following paragraphs, we describe change in categorical variables from a CFA perspective.

Analyzing change in categorical variables with Configural Frequency Analysis

Change in categorical variables implies moving from one category to another. Interindividual differences in such change imply that intraindividual development originates in the same category but goes on to different categories, over time. This is exemplified in Table 1.

In Table 1, Individual A transitions from Category a to Category from Time *i* to Time *j*. Individual B, in contrast, transitions from Category a to Category c. The same table can be used to illustrate multivariate change, that is, change in patterns addressed in the second tenet of person-oriented research. Suppose the category labels of the variable that spans the turnover tables in Table 1 represent patterns instead of single categories. Then, the transition from a to b is a transition from one multivariate pattern to a different one. Accordingly, the transition from a to c describes the transition from the same original pattern to a third pattern.

In Configural Frequency Analysis (CFA), a pattern is termed a *configuration*. Longitudinal CFA asks questions concerning the characteristics of transitions. In general, CFA asks questions concerning individual configurations. If a configuration is observed more often than expected, it is said to constitute a *CFA type*. If a configuration is observed less often than expected, it is said to constitute a *CFA antitype*. Based on von Eye & Gutiérrez-Peña (2004; cf. von Eye, Mair, & Mun, 2010), the statistical null hypothesis for a type/antitype decision can be formulated as follows.

Table 1:
Turnover Tables for Two Individuals

<table>
<tr><td></td><td></td><td colspan="3">Individual A</td><td colspan="3">Individual B</td></tr>
<tr><td></td><td></td><td colspan="3">Time j</td><td colspan="3">Time j</td></tr>
<tr><td></td><td colspan="4">Categories</td><td colspan="3">Categories</td></tr>
<tr><td rowspan="4">Time i</td><td></td><td>a</td><td>b</td><td>c</td><td>a</td><td>b</td><td>c</td></tr>
<tr><td>a</td><td></td><td>x</td><td></td><td></td><td></td><td>x</td></tr>
<tr><td>b</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>c</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Consider a two- or higher-dimensional cross-classification with R cells (configurations). For Configuration r, a test is performed under the null hypothesis H_0: E[m_r] = $\widehat{m_r}$, where m_r is the observed frequency of Configuration r, $\widehat{m_r}$ is the corresponding expected frequency, and E[.] indicates the expectancy. This null hypothesis proposes that Configuration r does not constitute a type or an antitype. If, however, Configuration r constitutes a CFA type, the null hypothesis is rejected because (using the binomial test for an example)

$$B_{N,\pi_r}(m_r - 1) \geq 1 - \alpha ,$$

where π_r indicates the probability of Configuration r. In other words, the null hypothesis is rejected because the cell contains more cases than expected. If Configuration r constitutes a CFA antitype, the null hypothesis is rejected because (again using the binomial test)

$$B_{N,\pi_r}(m_r) < \alpha .$$

This indicates that the null hypothesis is rejected because Cell r contains fewer cases than expected.

In longitudinal research, CFA identifies *types of constancy* and *types of changes*. Accordingly, there are *antitypes of constancy* and *antitypes of change*. A type or an antitype of constancy suggests that a particular temporal pattern that indicates no change was observed at a different rate than expected. A type or antitype of change suggests that a particular temporal pattern that indicates change was observed at a different rate than expected. Here, the terms constancy and change can refer to any parameter of series of measures.

The decision as to whether a configuration constitutes a type, an antitype, or is not suspicious is made with reference to the *CFA base model*. This model contains *all effects that* are *not of interest* to the researcher (von Eye, 2004). If this model is rejected, the effects the researcher is interested in must exist. The original CFA base model was that of variable independence (Lienert, 1968). This model takes all main effects into account, but no interactions of any order. Therefore, if the researcher is interested in interactions, the original base model is suitable. Most CFA base models are log-linear models (but other models have been discussed; see, e.g., von Eye, 2002). Consider, for example, the four variables A, B, C, and D. The log-linear base model of variable independence for these four variables is

$$\log \hat{m} = \lambda + \lambda^A + \lambda^B + \lambda^C + \lambda^D .$$

From a person-oriented research perspective, it is important to realize that the results of CFA are not expressed in terms of variable relationships. As can be concluded based on the CFA null hypothesis, the results of CFA are lists of type- or antitype-constituting configurations. Each of these reflects *local relationships*, that is, relationships that apply to patterns of variable categories, not necessarily to entire variables with all their categories (Havránek & Lienert, 1984).

A large number of CFA base models have been proposed for the analysis of longitudinal data (von Eye, 2002; von Eye, Mair, & Mun, 2010; von Eye, Mun, & Bogat, 2008, 2009). To introduce CFA models for longitudinal data, we present two models, the second of which being already suitable for the analysis of interindividual differences in intraindividual change. Later, in the next section, we show how lag analysis can be used for this purpose.

Consider the two variables X and Y, each observed twice to result in the four measures X1, X2, Y1, and Y2. One suitable base model for the longitudinal analysis of these four measures is

$$\log \hat{m} = \lambda + \lambda^{X1} + \lambda^{X2} + \lambda^{Y1} + \lambda^{Y2} + \lambda^{X1,Y1} + \lambda^{X2,Y2}.$$

This model proposes that, at Time 1, the two measures X1 and Y1 are associated, and that, at Time 2, they are associated again. This model can be rejected only if diachronous, that is, cross-time relationships between X and Y exist. In other words, this model can be rejected only if one or more of the following interactions exist: [X1, Y2], [X2, Y1], [X1, X2, Y1], [X1, X2, Y2], [X1, Y1, Y2], [X2, Y1, Y2], and [X1, X2, Y1, Y2]. Each of these terms reflects a particular diachronous interaction. Von Eye and Mair (2007, 2008) have proposed methods to determine which variable relationships cause types and antitypes in longitudinal CFA.

So far, the base models for original and longitudinal CFA did not distinguish between subgroups or even individuals. The model of longitudinal CFA just discussed can be respecified as conditional on the subjects under study. Specifically, let the first individual be labeled A and the second individual B. Then, the base model of longitudinal CFA is

$$\begin{aligned}\log \hat{m} &= \lambda + \lambda^{A} + \lambda^{X1|A} + \lambda^{X2|A} + \lambda^{Y1|A} + \lambda^{Y2|A} + \lambda^{X1,Y1|A} + \lambda^{X2,Y2|A} \\ &+ \lambda^{B} + \lambda^{X1|B} + \lambda^{X2|B} + \lambda^{Y1|B} + \lambda^{Y2|B} + \lambda^{X1,Y1|B} + \lambda^{X2,Y2|B}.\end{aligned}$$

This base model can be rejected for any of the following three reasons:

1. The interactions [X1, Y2], [X2, Y1], [X1, X2, Y1], [X1, X2, Y2], [X1, Y1, Y2], [X2, Y1, Y2], and [X1, X2, Y1, Y2] exist for Individual A;
2. The interactions [X1, Y2], [X2, Y1], [X1, X2, Y1], [X1, X2, Y2], [X1, Y1, Y2], [X2, Y1, Y2], and [X1, X2, Y1, Y2] exist for Individual B; and
3. synchronous or diachronous interactions exist that link Individual A with Individual B.

Types and antitypes that result from this base model may be hard to interpret. Therefore, researchers may wish to consider the following options. First, one can specify a base model that is saturated within both individuals. The resulting base model would be

$$\log \hat{m} = \lambda + \lambda^{A} + \lambda^{X1|A} + \lambda^{X2|A} + \lambda^{Y1|A} + \lambda^{Y2|A} + \lambda^{X1,Y1|A} + \lambda^{X2,Y2|A}$$
$$+\lambda^{X1,Y2|A} + \lambda^{X2,Y1|A} + \lambda^{X1,X2,Y1|A} + \lambda^{X1,X2,Y2|A} + \lambda^{X1,Y1,Y2|A} + \lambda^{X2,Y1,Y2|A} + \lambda^{X1,X2,Y1,Y2|A}$$
$$+\lambda^{B} + \lambda^{X1|B} + \lambda^{X2|B} + \lambda^{Y1|B} + \lambda^{Y2|B} + \lambda^{X1,Y1|B} + \lambda^{X2,Y2|B} + \lambda^{X1,Y2|B} + \lambda^{X2,Y1|B}$$
$$+\lambda^{X1,X2,Y1|B} + \lambda^{X1,X2,Y2|B} + \lambda^{X1,Y1,Y2|B} + \lambda^{X2,Y1,Y2|B} + \lambda^{X1,X2,Y1,Y2|B}$$

This model can be rejected only if interactions between Individuals A and B exist. These interactions can be either synchronous or diachronous. A second option would make this model more complex because all synchronous interactions between measures from the two individuals need to be included. Finally, a 2-group model can be considered in which one attempts to discriminate between the two individuals. This model would be

$$\log \hat{m} = \lambda + \lambda^{X1} + \lambda^{X2} + \lambda^{Y1} + \lambda^{Y2} + \lambda^{X1,Y1} + \lambda^{X2,Y2}$$
$$+\lambda^{X1,X2,Y1} + \lambda^{X1,X2,Y2} + \lambda^{X1,Y1,Y2} + \lambda^{X2,Y1,Y2} + \lambda^{X1,X2,Y1,Y2} + \lambda^{I},$$

where the last term distinguishes between the two individuals to be compared. This model is saturated in the four measures used for discrimination. It can be rejected only if any of the interactions between the individuals and the measures exists. Even if an interaction that discriminates between the two individuals is synchronous, it can be interpreted as developmental because the resulting statement would be that the two individuals differ at a particular point in time.

Configural Lag Analysis

Configural lag analysis (CLA; von Eye, Mair, & Mun, 2010) allows one to analyze *intensive longitudinal data* (Walls & Schafer, 2006). This type of data involves large numbers of repetitions and typically is created, in particular in psychological research, for relatively small numbers of cases (Nesselroade & Molenaar, 2010). To introduce the concept of a *lag*, let observations be made over T occasions, with $T > 2$. Then, an observation from a point in time $t + k,$ occurs with a k time units lag (for $t \leq T - k$, and $k > 0$). Accordingly, negative lags can be defined, with $k < 0$. An observation that takes place at a t - k time point occurred with a negative lag of k time units, that is, k time units before the observation at time t.

For data analysis, the string of observed measures is shifted up (for negative lags) or down (for positive lags), by k steps. This is illustrated for positive lags in Table 2 (cf. Table 11.3 in von Eye et al., 2010).

Two strings of measures, shifted by a lag of size k, can be crossed to create an I x I cross-classification, where I is the number of categories of the observed variable. This is illustrated in Table 3 (see von Eye et al., 2010; Table 11.4).

Table 2:
Longitudinal Measures with Lag 1, Lag 2, and Lag 3

Time	Original measures	Measures with Lag 1	Measures with Lag 2	Measures with Lag 3
1	x_1	-	-	-
2	x_2	x_1	-	-
.	.	x_2	x_1	-
.	.	.	x_2	x_1
.	.	.	.	x_2
		.	.	.
			.	.
				.
n -1	$x_{n\text{-}1}$	$x_{n\text{-}2}$	$x_{n\text{-}3}$	$x_{n\text{-}4}$
n	x_n	$x_{n\text{-}1}$	$x_{n\text{-}2}$	$x_{n\text{-}3}$

Table 3:
Cross-classification of a String of Scores, for a Lag of Size k

	Lag k Measures		
Original Measures	$I = 1$	$I = 2$	$I = 3$
$I = 1$	m_{11}	m_{12}	m_{12}
$I = 2$	m_{21}	m_{22}	m_{23}
$I = 3$	m_{31}	m_{32}	m_{33}

Similarly, strings from multiple lags can be cross-classified. For $k = 1$, the number of entries in a cross-classification of the type in Table 3 is reduced by 1. For $k = m$, the number of entries is reduced by m. This applies accordingly when more than one lag is considered simultaneously. In addition, the simultaneous analysis of lagged information with time-invariant information such as Gender is straightforward. The interpretation of the entries in cross-classifications like the one exemplified in Table 3 is without problems. Entry ij (for $i, j = 1, ..., I$) in this cross-classification indicates the frequency with which an observation of Category i at time t was preceded by an observation of Category j, at Time t - k.

Base models for CLA can be specified using the same criteria as for standard CFA. Consider, for example, the case in which two strings of data are available, for the two individuals A and B. The second string results from a shift by k time units. Let the original observations be labeled with O, and the lagged observations with K. Then, the base model of original CFA which proposes variable independence is

$$\log \hat{m} = \lambda + \lambda^{ID} + \lambda^{O} + \lambda^{K} ,$$

where *ID* indicates the variable that distinguishes the two individuals. Types and antitypes from this model suggest local associations between the variables *ID*, *O*, and *K*. More pertinent to longitudinal research are the following two models. First, we ask whether the two respondents differ in their lag structure. The base model for this question includes the association between *O* and *K*, but proposes independence of *ID*, *O*, and *K*, or

$$\log \hat{m} = \lambda + \lambda^{ID} + \lambda^{O} + \lambda^{K} + \lambda^{O,K}$$

This model can be rejected only if any of the interactions [*ID*, *O*], [*ID*, *K*], and [*ID*, *O*, *K*] exist. Types and antitypes from this base model suggest that the respondents differ either in their development over time (two-way interactions) or in the development of their patterns of constancy and change, over a lag of *K* (three-way interaction). In its structure, this base model is identical to the base model of 2-group CFA (cf. von Eye, 2002).

Taking also into account that the two respondents may differ in their temporal pattern of behavior both in the original and the lagged string, the model

$$\log \hat{m} = \lambda + \lambda^{ID} + \lambda^{O} + \lambda^{K} + \lambda^{O,K} + \lambda^{ID,O} + \lambda^{ID,K}$$

may be considered. If this model is rejected, only the interaction [*ID*, *O*, *K*] can exist. Types and antitypes from this base model suggest that the two respondents differ in their pattern of constancy and change over a lag of size *K*.

Data example

In this section, we illustrate CLA using data from a project on the development of alcohol use disorders (Perrine, Mundt, Searles, & Lester, 1995) in adulthood. A sample of self-diagnosed alcoholic males provided information about their drinking the day before, and their subjective ratings of mood, health, or quality of the day every morning. Here, we ask, whether the drinking pattern of Respondent 3000 differs from the drinking pattern of Respondent 3004. We use a lag of seven to assess drinking constancy and change in a weekly rhythm. The interesting aspect of lagged configural analysis of seven days is that the corresponding days in each week are used. Respondent 3000 provided data for 735 consecutive days. Respondent 3004 did the same for 742 consecutive days. Here, we focus on the consumption of beer.

In preliminary analyses, we found that these two respondents display quite different drinking behavior (see von Eye & Bergman, 2003). The drinking pattern of Respondent 3000 is erratic in the sense that there is no strong autocorrelation structure that can be linked to weekdays, months, or any other calendar patterns. Respondent 3004 is quite the opposite. His drinking is predictable over very long stretches of time. Not one of his autocorrelations is non-significant. Even for a lag of k = 50, the autocorrelation is stronger than 0.50. In contrast, not a single autocorrelation of Respondent 3000 reaches

0.30, not even for the shorter intervals. The two respondents also differed in the number of beers they consumed. Over the entire observation span, Respondent 3000 consumed an average number of 1.1 beers per day, with a range from 0 and 9 beers. Respondent 3004 consumed, on average, 5.1 beers per day, with a range from 0 to 14. Both respondents consumed liquor in addition (not analyzed here). Figure 3 displays the autocorrelation patterns of the two respondents.

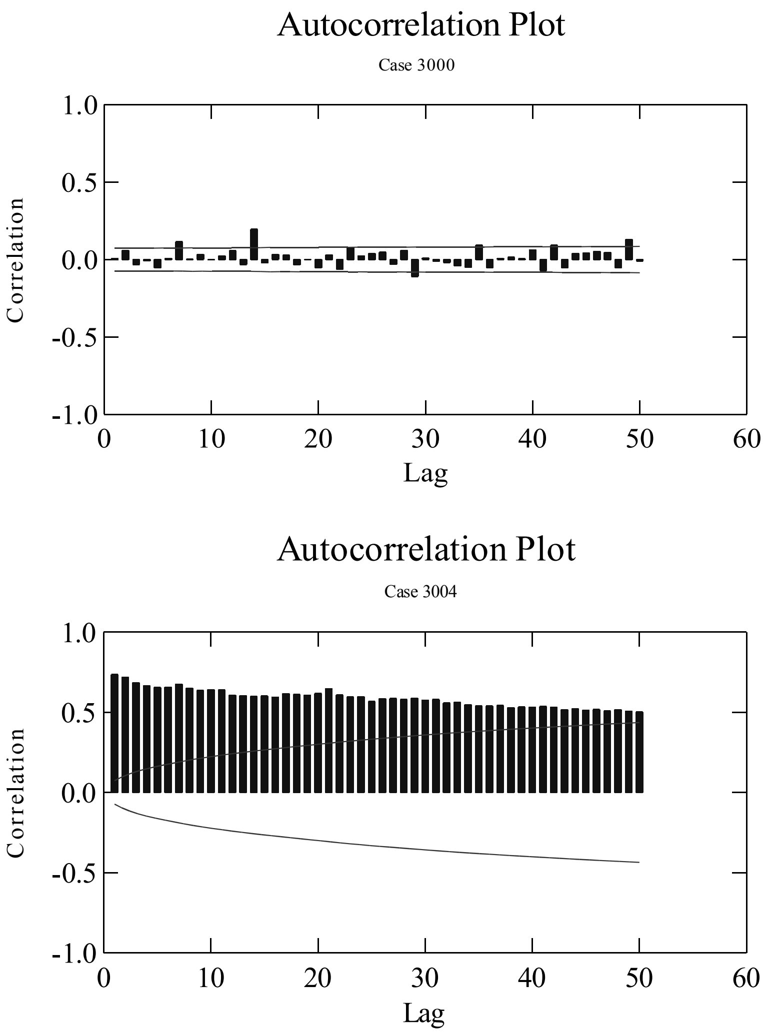

Figure 3:
Autocorrelation patterns of the beers consumed by Respondent 3000 and Respondent 3004

For the following log-linear and configural analyses, we winsorized the frequencies of beer use. This was done to prevent the cross-classifications from becoming overly sparse. Respondent 3000 never had more than 9 beers on any given day. Therefore, we created a category that represents "9 or more beers on a single day." The number-of-beers-consumed variable (*B*) is, therefore, no longer ratio but ordinal scale. It has 10 categories, ranging from 0 through 9. The following analyses examine the 2 (*ID*) x 10 (*B*) x 10 (*B7*) cross-classification given in the appendix, where *B7* indicates beer consumption with a lag of seven days. We consider three log-linear models. The first is the main effect model of variable independence,

$$\log \hat{m} = \lambda + \lambda^{ID} + \lambda^{B} + B^{B7} .$$

Types and antitypes from this model suggest local associations between the variables *ID*, *B*, and *B7*. The second model considered here asks whether the two respondents differ in their lag structure. The base model for this question includes the association between *B* and *B7*, but proposes independence of *ID*, *B*, and *B7*, that is,

$$\log m = \lambda + \lambda^{ID} + \lambda^{B} + \lambda^{B7} + \lambda^{B,B7} .$$

This model can be rejected only if any of the interactions [*ID*, *B*], [*ID*, *B7*], and [*ID*, *B*, *B7*] exists. Types and antitypes from this base model suggest that the two respondents differ either in their longitudinal pattern of beer drinking over time (two-way interactions) or in the development of their longitudinal patterns of constancy and change in beer drinking, over a lag of $K = 7$ (three-way interaction).

The third model takes into account that the two respondents may differ in their temporal pattern of beer drinking both in the original series of observations and the lagged observations. This is the model

$$\log m = \lambda + \lambda^{ID} + \lambda^{B} + \lambda^{B7} + \lambda^{ID,B} + \lambda^{ID,B7} + \lambda^{B,B7}$$

If this model is rejected, only the interaction [*ID*, *B*, *B7*] can exist. Types and antitypes from this base model suggest that the two respondents differ in their pattern of constancy and change in beer drinking over a lag of size *K* for a span of over two years of daily observations.

The first of these three models comes with a goodness-of-fit $G^2 = 2217.75$ ($df = 180$; $p < 0.01$). This large value indicates that there are strong relationships in the three-way table. From a configural perspective, we ask where, in the table, the biggest deviations can be found. In this example, the biggest deviations, in units of standardized deviates, suggest weekday-specific stability. The biggest deviation constitutes a type. It is found in Cell 8 8, for Respondent 3004. For 32 of the 742 observation days as well as for the corresponding day one week later, Respondent 3004 had indicated that he consumed 8 beers. Under the main effect base model of variable independence, 4.15 days had been expected ($z = 13.67$; $p < \alpha^*$). This type suggests drinking behavior that is stable for the same day in consecutive weeks. The second biggest deviation, also indicating a type, was also found for Respondent 3004, for Cell 8 9. This configuration indicates drinking behavior that is close to stable. Eight beers on one weekday are followed by 9 or more beers on the same day of the next week. Similarly, the strongest deviation for Respondent 3000 also indicates a stability type. It is found for Configuration 1 1. For 169 of the 735 observation days and the corresponding same weekday one week later, Respondent 3000 indicated that he had not consumed any beer. Under the main effect base model, 76.74 days had been expected.

In general, most of the (near-) stability types for Respondent 3000 were found for corresponding days on which this respondent consumed no beer or only small numbers of beers. For Respondent 3004, the opposite was true. (Near-) stability types were found for the corresponding days on which he consumed 5 or more beers.

Only a few configurations constituted antitypes. These were all configurations that describe corresponding days for Respondent 3000 on which he leaped from drinking nothing to drinking 7 or more beers. The same applies for Respondent 3004.

From the perspective of studying interindividual differences in intraindividual change, more interesting is the direct comparison of the beer drinking patterns of the two respondents. The second of the above three base models allows one to perform such a comparison. The goodness-of-fit $G^2 = 1033.71$ ($df = 99$; $p < 0.01$) for this model suggests that this model is significantly better than the original base model ($\Delta G^2 = 1184.04$; $\Delta df = 81$; $p < 0.01$). It should be noted, however, that both of the programs we used to analyze the frequency table in the appendix (Lem and SYSTAT 13) indicated convergence problems. Here, we interpret the solution provided by Lem (Vermunt 1993), because even the Delta option, invoked with $\Delta = 0.05$, did not improve the solution provided by SYSTAT (cf. the discussion of computational issues in log-linear modeling in von Eye & Mun, 2012). The issue was that a number of cell frequencies were estimated to be near zero, which caused the program to have problems estimating parameters for these cells.

Still, model fit is poor and we tentatively inspect the differences between the observed and the expected cell frequencies and the corresponding standardized residuals to identify the largest differences between the two respondents. We find that, as for the original base model, the largest discrepancies come in the form of types, and they suggest stable drinking behavior over the observation period of more than two years. Specifically, Respondent 3000 shows stability mostly in the domain of no drinking or drinking only small numbers of beers. In the domain of drinking large numbers of beers, we find stability antitypes. The strongest of these suggests that this respondent drinks 7 beers on a given day as well as the corresponding day one week later at a rate far lower than expected. In fact, this pattern was not reported at all (see the table in the appendix). The same applies to (not) consuming 9 beers or more.

In contrast, Respondent 3004 shows an antitype that is constituted by Cell Configuration 1 1. This antitype suggests that this respondent reported significantly fewer corresponding non-drinking days than expected (84 versus 127.02). Clearly this difference goes in the opposite direction as for Respondent 3000, and it is significantly stronger for respondent 3000. The other discrepancies are similar to the ones found with the original base model. Respondent 3004 is more stable than Respondent 3000 when it comes to reporting the consumption of large numbers of beers (7 and more), and Respondent 3000 is more stable than his counterpart when it comes to reporting the consumption of small numbers of beers, or none. No additional antitypes emerged from this base model.

Considering that the development of beer drinking may be specific to the respondent (third base model) yields a different picture. The overall goodness-of-fit for this model was $G^2 = 92.33$ ($df = 81$; $p = 0.18$). This result suggests that this model is not only significantly better than the first base model ($\Delta G^2 = 2125.42$; $\Delta df = 99$; $p < 0.01$), but it can also stand for itself and describes the data well. The three-way interaction between the three variables that span the cross-classification in the appendix is not needed to explain the frequencies. In the context of hierarchical log-linear models, this base model would be saturated anyway, and no types or antitypes could possibly result.

We conclude that the differences between Respondent 3000 and Respondent 3004 can be satisfactorily explained by the respondent-specific constancy and change in alcohol consumption. The differences in the one week lags are not needed to describe the interindividual differences in intraindividual change between these two respondents.

Discussion

From the perspective person-oriented research, the study of interindividual differences in intraindividual change is most interesting and important. There exist, unfortunately, only small numbers of empirical projects that create data that allow one to undertake such comparisons. In most cases, intensive longitudinal data as described by Walls and Schafer (2006) are needed for such comparisons. Most of the small number of published works on interindividual differences in intraindividual change are either theoretical (Baltes, Reese, & Nesselroade, 1977) or methodological (Nesselroade & Molenaar, 2010, von Eye et al., 2010). Empirical papers exist in which P-technique and related methods are applied mostly to physiological and mood data (for an overview, see Jones & Nesselroade, 1990).

Interestingly, P-technique and related methods carry strong variable-oriented elements even when they are applied in person-oriented research. These elements are that statements are made under the assumption that variable relationships exist and are valid for the entire range of admissible scores. The approach presented in this article shows that this assumption may not always hold. We found that the model of all two-way interactions explains the data well. However, the two-way interactions are not carried by all levels of drinking. Specifically, we found that the differences between the two respondents are most evident at the extreme levels, that is, for zero or small numbers of beers consumed (Respondent 3000) and for seven or more beers (Respondent 3004). In between these numbers, the observed frequencies do not differ from those estimated, even for the base model of variable independence. We conclude that *local associations* as defined by Havránek and Lienert (1984) can be identified, in particular, when a configural approach is adopted.

Two issues of concern should not be overlooked. The first may be specific to the data used for the example in this article, and the second is more general in nature. The first issue concerns the nature of data that can make it hard for computer programs to estimate models. In the present data example, both the column and the row that are constituted by having consumed eight beers are empty, for Respondent 3000. As soon as interactions are estimated that involve this respondent, this pattern causes problems, and generally available, even commercially available software report problems with convergence. For example, Lem reported, for the third of the above base models, eight (nearly) boundary or non-identified (log-linear) parameters and 29 zero estimated frequencies. In contrast, SYSTAT reports that the solution to this problem is not unique and gives an overall goodness-of-fit result of $G^2 = 3247.48$ ($df = 164$; $p < 0.01$). This result is dramatically different than the result given by Lem, and this difference cannot be explained by rounding. Instead, these differences reflect the way the programs handle the problem of estimating frequencies to be zero. We, therefore, recommend that researchers recalculate their results using different programs, to make sure that published results are data-specific instead of reflecting software peculiarities.

The second issue is statistical. It is concerned with the assumptions made about the independence of data in frequency tables such as the one in the appendix. This issue is important because it concerns most of the longitudinal models that are estimated for log-linear models or CFA. Assuming independence between the observations of the same individual in longitudinal studies is rather common (it simplifies things), but may have some undesirable consequences. Liang and Zeger (1986) consider independence a *working assumption*, but also consider some alternatives. To the best of our knowledge, the modern approach to dealing with the lack of independence is to assume that independence holds, but *conditional on a latent process* (or latent random variable). This approach seems to work but may be difficult to implement. Further work is required in data analysis under this assumption.

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Appendix

Cross-classification Respondent x Number-of-beers-consumed x Number-of-beers-consumed on the corresponding day in the following week

Observed Frequencies

IDNUMBER	BEER1	BEER7									
		0	1	2	3	4	5	6	7	8	9
3,000	0	169	65	50	28	15	7	4	1	0	0
	1	81	37	25	18	3	1	0	0	0	0
	2	44	35	17	11	8	1	1	0	0	1
	3	22	17	18	4	2	0	0	0	0	0
	4	18	7	2	0	0	0	1	0	0	0
	5	2	2	4	0	0	0	0	0	0	0
	6	2	1	1	2	0	0	0	0	0	0
	7	0	0	1	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0	0	0
	9	0	1	0	0	0	0	0	0	0	0
3,004	0	84	15	16	9	5	2	2	1	1	1
	1	21	4	3	2	0	0	0	1	0	1
	2	11	6	2	2	1	2	4	4	3	1
	3	9	3	1	3	1	0	6	2	2	1
	4	2	1	2	3	3	5	15	3	3	5
	5	3	1	2	4	7	10	14	5	14	4
	6	1	0	3	3	10	11	29	21	20	17
	7	1	2	2	0	5	11	12	19	17	16
	8	2	0	2	2	4	10	18	16	32	24
	9	3	1	1	0	6	13	15	13	18	17