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Longitudinal Configuration Frequency Analysis as Special Case of the CFA - Illustrated with data on depression incidences in Bavaria between 2007 and 2012[1]

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Abstract

The Configuration Frequency Analysis (CFA) by Krauth & Lienert (1973) was originally developed for the identification of cross-sectional types and syndromes of an array of discrete variables designated as configurations. However, a longitudinal CFA variant on arrays composed of repeated observations of a discrete variable was already discussed in the original publication. In later work, Lienert chose to call this variant configuration trajectory analysis (German: Konfigurationsverlaufsanalyse, KVA), while recent text books introduced the term Longitudinal CFA (L-CFA). The L-CFA is characterized by a robust person-oriented analysis of trajectory types and provides a descriptive overview on types and antitypes in a longitudinal data set. We are illustrating the utility of the L-CFA in two large data sets of the health insurance company AOK Bayern testing the hypothesis of increasing depression risk during the time period between 2007 and 2012 by searching for typical and antitypical trajectories of depression incidence rates among Bavarian citizens.

Keywords: Configuration Frequency Analysis, person-oriented approach, longitudinal design, depression, somatic disorders

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Gustav A. Lienert's methodological heritage includes a rich collection of versatile tools for the non-parametric analysis of cross-sectional and longitudinal data. The Configuration Frequency Analysis (CFA) is in the center of this collection. It was originally introduced by Lienert in 1968 at the biannual conference of the German Society for Psychology (Lienert, 1969), published in a series of articles (Lienert, 1970, 1971a, 1971b, 1971c, 1972), and, together with Joachim Krauth, as a text book (Krauth & Lienert, 1973).

The CFA was developed for the identification of types and antitypes of an array of discrete variables, which are denoted as configurations. The conceptual idea behind this method was inspired by the clinical concept of a drug induced psychosis typically resulting in a "psychotoxic" symptom pattern (Leuner, 1962) and by P.E. Meehl's work on configural pattern scoring (Meehl, 1950) documenting the presence of a three-way interaction despite absence of two-way interactions under certain circumstances. Combining both approaches, Lienert suggested the aggregation of binary variables (e.g., presence vs. absence of certain symptoms) into configurations to reveal type patterns that occur more frequent than expected under the null hypothesis of independency of the binary variables.

Lienert's intention for the CFA was to provide a general method for the identification and classification of types or syndromes across a set of variables of all scale levels within an inhomogeneous sample of individuals that can be easily tested for statistical significance. Beyond this classical approach, the CFA was further developed for additional scenarios including the identification and classification of longitudinal change types composed of repeated observations of a discrete variable. These change types were denoted as symptom shift types, and the corresponding analysis was introduced as CFA for repeated measures designs (Krauth & Lienert, 1973). In his later work, Lienert chose to call this variant configuration trajectory analysis (German: Konfigurationsverlaufsanalyse, KVA), while recent text books introduced the term Longitudinal CFA (L-CFA) (Stemmler, 2020), which we are further using in this article. We are illustrating use and utility of the L-CFA in two large data sets of the health insurance company AOK Bayern by testing the popular hypothesis of assuming an increasing depression risk during recent times. First, however, we are starting with a brief introduction to concept and methodology of the classical CFA.

Configuration Frequency Analysis

The Configuration Frequency Analysis (CFA) is a versatile and easily applicable tool for analyzing multidimensional contingency tables by generating an array of discrete variables, which are designated as configurations. The CFA is basically a distribution-free approach; however, the convenient CFA analysis employs X^2-tests for comparing observed with expected frequencies for the generated configurations. Table 1 presents

a configuration table template for the patterned frequencies of the three binary variables A, B, and C, each comprising "+" and "-" as possible values. The number of configurations k is $2^3 = 8$ determined by value number to the power of variable number.

Table 1. CFA table template for patterned frequencies of the three dichotomous variables A, B, C.

Configuration	Frequencies		
A B C	observed (o)	expected (e)	$X^2_{df=1}$
+ + +	o_{+++}	e_{+++}	X^2_{+++}
+ + -	o_{++-}	e_{++-}	X^2_{++-}
+ - +	o_{+-+}	e_{+-+}	X^2_{+-+}
+ - -	o_{+--}	e_{+--}	X^2_{+--}
- + +	o_{-++}	e_{-++}	X^2_{-++}
- + -	o_{-+-}	e_{-+-}	X^2_{-+-}
- - +	o_{--+}	e_{--+}	X^2_{--+}
- - -	o_{---}	e_{---}	X^2_{---}
	Σ N	Σ N	$X^2_{df=k-1}$

Note. X^2 = chi-square statistic; *df* = degree of freedom; *k* = number of configurations.

Under the assumption of independence of the three variables A, B, and C (null hypothesis, H_0), the expected frequency e_{abc} of each configuration results from the marginal distribution of the involved variables reflecting their main effects without interactions between them:

$$e_{abc} = \frac{n_{a..} * n_{.b.} * n_{..c}}{N^2},$$

with $n_{a..}$, $n_{.b.}$, $n_{..c}$ sums of the respective A, B, and C values, and *N* the total number of observations.

The convenient test of significance for the overall configuration table with k configurations is a Pearson X^2 test:

$$X^2_{df} = \sum_{abc=+++}^{---} \frac{(o_{abc} - e_{abc})^2}{e_{abc}},$$

with degrees of freedom (df) = k – 1.

In case of significance of the overall configuration table, each individual configuration can be tested post-hoc for types and antitypes, which can also be performed with a Pearson X^2 - test with one degree of freedom:

$$X^2_{df=1}(abc) = \frac{(o_{abc} - e_{abc})^2}{e_{abc}}$$

In Table 2, Lienert's CFA data example on Leuner's psychotoxic syndrome (Krauth & Lienert, 1973) in response to an experimentally induced psychosis in healthy subjects is presented. The syndrome includes three independent features B ("Bewusstseinseintrübung"), D ("Denkstörung"), and A ("Affektivitätsbeeinflussung"), with „+" indicating presence and "-" absence of the respective feature. The resulting configurations can be seen in Table 2.

Table 2. CFA table of Lienert's LSD data set (Krauth & Lienert, 1973).

Configuration	Frequencies		
B D A	observed	expected	$\boldsymbol{X^2_{df=1}}$
+ + +	20	12.51	4.491 -
+ + -	1	6.85	4.995 -
+ - +	4	11.40	4.805 -
+ - -	12	6.24	5.306 -
- + +	3	9.46	4.415 -
- + -	10	5.18	4.479 -
- - +	15	8.63	4.704 -
- - -	0	4.73	4.725 -
	Σ 65	Σ 65	$\boldsymbol{X^2_{df=7}}$ = 37.92, p < .001

Note. X^2 = chi-square statistic; *df* = degree of freedom.

The overall configuration table reaches a X^2 score of 37.92 with df = 7, which is highly significant ($p < .001$). The „+++" configuration representing the psychotoxic syndrome shows the highest observed frequency deviating from the expected frequency with nominal statistical significance at the 5%-level ($p_{uncorrected} = .034$) likewise all other configurations ($X^2_{df=1}(p = .05) = 3.842$). Configuration frequencies significantly deviating from the expected frequency are denoted as types when occurring more frequently and as antitypes when occurring more rarely than expected. However, the repeated evaluation of single configurations requires measures to maintain the overall significance threshold for all post-hoc tests by applying an appropriate

correction for multiple testing, e.g., the Bonferroni correction, i.e., dividing the nominal significance threshold by the number of applied simultaneous tests. In the data example from Table 2 eight configurations are tested post-hoc; when using the Bonferroni-correction, the critical $X^2_{df=1}\left(p = \frac{0.05}{8}\right)$ threshold increases to 7.477, which means that no configuration deviates significantly from the expected frequency after correction for multiple testing.

Longitudinal Configuration Frequency Analysis (L-CFA)

The Longitudinal Configuration Frequency Analysis (L-CFA) is a special case of the first order CFA (cf. Stemmler, 2020). While the CFA was originally developed for the identification of cross-sectional types and syndromes, configurations in the L-CFA variant are composed of repeated observations of a discrete variable. For example, a configuration might include data collected at three time points T_1, T_2 and T_3. Table 3a shows the corresponding L-CFA table template.

The statistical analysis is complementary to that of the regular CFA. Expected frequencies are calculated under the null-hypothesis of independent observations. In addition to the test of the overall table, post-hoc tests for types and antitypes are performed at the configuration level. As for the regular CFA, measures to maintain the overall significance threshold for all post-hoc tests are required by applying an appropriate correction for multiple testing.

An advantage of the L-CFA is the option of condensing configurations by using measures of change instead of repeated observations. When using the change score signs between consecutive pairs of the time points T_1, T_2 and T_3, e.g., "+" for increases, "-" for decreases, with steadiness allocated to one of the two change categories depending on the null hypothesis, the resulting number of configurations can be reduced from eight to four (see Table 3b) allowing a more efficient testing for types and antitypes due to the reduced number of simultaneous post-hoc tests.

A disadvantage of the L-CFA, specifically, in combination with the use of change scores, is the inherent dependency of repeated observations. These effects are not addressed in the typical calculation of the expected frequencies, which means that the detection of types and anti-types might be biased by these dependencies. This bias, however, can be diminished by method and design adjustments, e.g., by increasing intervals between observations or by using sensitive measures with a large range of values.

Table 3a. L-CFA table template for a dichotomous variable at three time points T_1, T_2, T_3.

Configuration	Frequencies		
$T_1T_2T_3$	observed (o)	expected (e)	$\boldsymbol{X^2_{df=1}}$
+ + +	o_{+++}	e_{+++}	X^2_{+++}
+ + -	o_{++-}	e_{++-}	X^2_{++-}
+ - +	o_{+-+}	e_{+-+}	X^2_{+-+}
+ - -	o_{+--}	e_{+--}	X^2_{+--}
- + +	o_{-++}	e_{-++}	X^2_{-++}
- + -	o_{-+-}	e_{-+-}	X^2_{-+-}
- - +	o_{--+}	e_{--+}	X^2_{--+}
- - -	o_{---}	e_{---}	X^2_{---}
	Σ N	Σ N	$\boldsymbol{X^2_{df=k-1}}$

Note. X^2 = chi-square statistic; *df* = degree of freedom; *k* = number of configurations.

Table 3b. L-CFA template from Table 3a after converting repeated observations into consecutive dichotomous change score $D_{2\text{-}1}$, $D_{3\text{-}2}$.

Configuration	Frequencies		
$D_{2\text{-}1}D_{3\text{-}2}$	observed (o)	expected (e)	$\boldsymbol{X^2_{df=1}}$
+ +	o_{++}	e_{++}	X^2_{++}
+ -	o_{+-}	e_{+-}	X^2_{+-}
- +	o_{-+}	e_{-+}	X^2_{-+}
- -	o_{--}	e_{--}	X^2_{--}
	Σ N	Σ N	$\boldsymbol{X^2_{df=k-1}}$

Note. X^2 = chi-square statistic; *df* = degree of freedom; *k* = number of configurations.

Depression development over time

Statistical data from health insurances show a continuous increase in the number of sick leave days due to depression and other mental illnesses over the past 25 years (Marschall, 2020), with numbers almost doubling between 2006 and 2014. At the same time, the proportion of people receiving pensions for reduced earning capacity due to mental disorders has more than doubled (Deutsche Rentenversicherung Bund, 2021) with depression diagnoses the leading cause among all mental disorders. These statistical data contrast with epidemiological research findings using population-representative diagnostic surveys that provide no evidence of a substantial increase in mental illnesses during this period compared with prior assessments (Baxter et al., 2014; Jacobi et al., 2014; Wittchen et al., 2011).

Inspecting the development of real-life diagnostic data during this time span might shed light to the true development of depression incidences. For this purpose, we kindly received access to anonymized diagnostic data from AOK Bayern. AOK Bayern is a public health care insurance company with more than 4.5 million clients in Bavaria, Germany.

Two longitudinal age cohorts of anonymized Bavarian residents were randomly drawn in the context of an earlier research project of the Max Planck Institute of Psychiatry together with the AOK Bayern, providing diagnostic data for the time period between the years 2007 and 2013. These two cohorts included 35,000 individuals born between the years 1970 to 1981 (younger cohort, aged between 26 and 37 years at baseline), and 31,205 individuals born between the years 1950 to 1961 (older cohort, between 46 and 57 years at baseline). From these two cohorts, all diagnoses obtained from different medical facilities including general practitioners, medical specialists, and hospitals were analyzed. Presence vs. absence of a depression diagnosis (major depression, ICD-10 code F32; recurrent depression, F33; persistent mood disorders, F34) were coded per year; in addition, presence vs. absence of any major somatic diagnosis (cancer, C00 - D48; endocrine, nutritional or metabolic disorders, E00 - E90; cardiovascular disorders, I00 - I99; respiratory disorders, J00 - J99; digestive disorders, K00 - K93; musculoskeletal or connective tissue disorders, M00 - M99) was also annually coded. This coding procedure resulted in individual time series of annual depression diagnoses and major somatic diagnoses (presence vs. absence) between the years 2007 and 2013 for both cohorts.

L-CFA on the Depression Diagnoses Development in Bavaria

Taking advantage from the longitudinal character of the dataset, we calculated "change scores" between consecutive years by coding "+" for the incidence of a diagnosis in the following year, and "-" for no change or absence of a previous diagnosis in the following year. To avoid dependencies between the generated change scores,

we skipped every subsequent comparison, resulting in three quasi-independent comparisons D_1 for 2007 vs. 2008, D_2 for 2009 vs. 2010, and D_3 for 2011 vs. 2012 with "+" for incidence of a diagnosis and "-" for no change or absence of a previous diagnosis in the following year. The resulting L-CFA table for the evaluation of change trajectories in depression incidences is presented in Table 4 separately for the younger and the older cohort. Expected frequencies are calculated under the null-hypothesis of independent observations. Post-hoc tests for detecting types and antitypes were Bonferroni-corrected for eight simultaneous tests, resulting in a critical $X^2_{df=1}\left(p = \frac{0.05}{8}\right)$ threshold of 7.477. All analyses were programmed and performed using Microsoft Excel 2019.

Table 4. L-CFA on the incidence of a depression diagnosis during three pairs of consecutive years, 2007 vs. 2008 (D_1), 2009 vs. 2010 (D_2), and 2011 vs. 2012 (D_3).

Configuration	Younger Cohort (1970-81)				Older Cohort (1950-61)			
$D_1D_2D_3$	observed	expected	$X^2_{df=1}$		observed	expected	$X^2_{df=1}$	
+ + +	12	1.04	115.65	T	10	1.97	32.74	T
+ + -	58	30.09	25.88	T	89	44.59	44.23	T
+ - +	63	31.40	31.81	T	80	48.28	20.83	T
+ - -	839	909.47	5.46	-	1009	1093.16	6.48	-
- + +	85	36.37	65.02	T	104	49.76	59.11	T
- + -	966	1053.50	7.27	-	1020	1126.67	10.10	A
- - +	1008	1099.19	7.57	A	1126	1219.98	7.24	-
- - -	31969	31838.94	0.53	-	27767	27620.58	0.78	-
	Σ 35.000	Σ 35.000	X^2_7 = 259.2, p < .001		Σ 31.205	Σ 31.205	X^2_7 = 181.5, p < .001	

Note. X^2 = chi-square statistic; *df* = degree of freedom; *T* = type, *A* = antitype, i.e., significant post-hoc test after Bonferroni correction.

The overall X^2 tests for the configuration tables of both cohorts are highly significant ($p < .001$) indicating a deviation of the observed from the expected change configurations. And indeed, all configurations indicating the incidence of a depression diagnosis in at least two of the three consecutive comparisons are significantly overrepresented as types in both cohorts. In addition, one antitype with a singular incidence of a depression diagnosis in the second or third comparison was present in the older and

younger cohort, respectively. Interestingly, the number of individuals with no incidence of a diagnosis (= "---" configuration) was well in accordance with the expected frequency under the null hypothesis of no change.

Finally, we tested the specificity of the observed L-CFA findings for depression by generating corresponding configurations for the incidence of any major somatic diagnosis in the following year using the same quasi-independent comparisons D_1 for 2007 vs. 2008, D_2 for 2009 vs. 2010, and D_3 for 2011 vs. 2012. The resulting change configurations for incidences of somatic diagnoses are presented in Table 5 separately for the younger and the older cohort. Expected frequencies are calculated under the null-hypothesis of independent observations. Post-hoc tests for detecting types and antitypes were Bonferroni-corrected for eight simultaneous tests, resulting in a critical $X^2_{df=1}\left(p = \frac{0.05}{8}\right)$ threshold of 7.477.

The obtained pattern of findings is almost identical with the one observed for depression incidences. The overall X^2 tests for the configuration tables of both cohorts is highly significant ($p < .001$), and all configurations indicating the incidence of a somatic diagnosis in at least two of the three consecutive comparisons are significantly overrepresented as types in both cohorts. All configurations with a singular incidence of a somatic diagnosis in any of the three comparisons are antitypes indicating lower occurrence than expected. The number of individuals with no incidence of a somatic diagnosis (= "---" configuration) was again well in accordance with the expected frequency under the null hypothesis of no change.

In summary, the L-CFA unequivocally revealed that change configurations indicating the incidence of a diagnosis in at least two of three consecutive comparisons are typical for the development of clinical diagnoses in Bavarian AOK insured citizens between the years 2007 and 2012. This pattern is not specific to the incidence of depression, but could be likewise observed for the incidence of any major somatic disorder. The same pattern could be observed in the younger cohort of citizens initially aged between 26 and 37 as well as in an older cohort with an initial age range between 46 and 57. Thus, the observed type pattern of change is not specific for depression and can be observed in either age cohort.

Table 5. L-CFA on the incidence of a somatic diagnosis during three pairs of consecutive years, 2007 vs. 2008 (D_1), 2009 vs. 2010 (D_2), and 2011 vs. 2012 (D_3).

Configu-ration	Younger Cohort (1970-81)				Older Cohort (1950-61)			
$D_1D_2D_3$	ob-served	expected	$X^2_{df=1}$		ob-served	expected	$X^2_{df=1}$	
+ + +	73	30.97	57.06	T	28	7.80	52.32	T
+ + -	383	295.97	25.59	T	191	147.62	12.75	T
+ - +	335	285.10	8.74	T	165	104.36	35.23	T
+ - -	2546	2724.97	11.75	A	1851	1975.22	7.81	A
- + +	366	293.81	17.74	T	189	101.10	76.42	T
- + -	2607	2808.26	14.42	A	1762	1913.48	11.99	A
- - +	2541	2705.13	9.96	A	1184	1352.74	21.05	A
- - -	26149	25855.80	3.32	-	25835	25602.68	2.11	-
	Σ 35.000	Σ 35.000	X^2_7 = 148.6, p < .001		Σ 31.205	Σ 31.205	X^2_7 = 219.7, p < .001	

Note. X^2 = chi-square statistic; *df* = degree of freedom; *T* = type, *A* = antitype, i.e., significant post-hoc test after Bonferroni correction.

Summary and Discussion

The L-CFA results indicate that the incidence of a diagnosis in at least two of three consecutive comparisons between 2007 and 2012 is typical for the development of depression, but also for any major somatic disorder. While the initial hypothesis of increasing depression diagnoses during the observation period cannot be rejected, this development seems to be unspecific and not typical for depression alone. In addition, the same trajectory pattern could be equally observed in the younger and in the older cohort suggesting an age-independent general trend. Nevertheless, the "---" configuration of no change in diagnosis during the observation period showed by far the highest frequencies across all analyses, which do not deviate from the expected frequency under the null hypothesis of no change. This finding corresponds with the results of a quantitative trend analysis recently presented by the first author (Lang, 2019).

There is a number of advantages linked to the use of L-CFA in longitudinal datasets: (1) L-CFA is applicable to repeated observations of all scale levels, (2) it is basically distribution-free, and (3) L-CFA follows a person-oriented approach, i.e., directly identifies the individual cases from the crosstabulation contributing to the observed pattern of types and antitypes. This enables a direct exploratory inspection of case characteristics potentially driving the observed effects. (4) Finally, breaking longitudinal trajectories down into categorical configurations facilitates an easy and unambiguous interpretation of findings, even in complex data sets.

Gustav A. Lienert's intention was to develop and present statistical methods that are easy to apply, easy to interpret, robust, and applicable also in small datasets. CFA and the L-CFA are typical examples for Lienert's methodological heritage. It would be desirable, and certainly in his spirit, if configural approaches like the L-CFA would become more popular and would be more widely used in psychology and medicine.

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