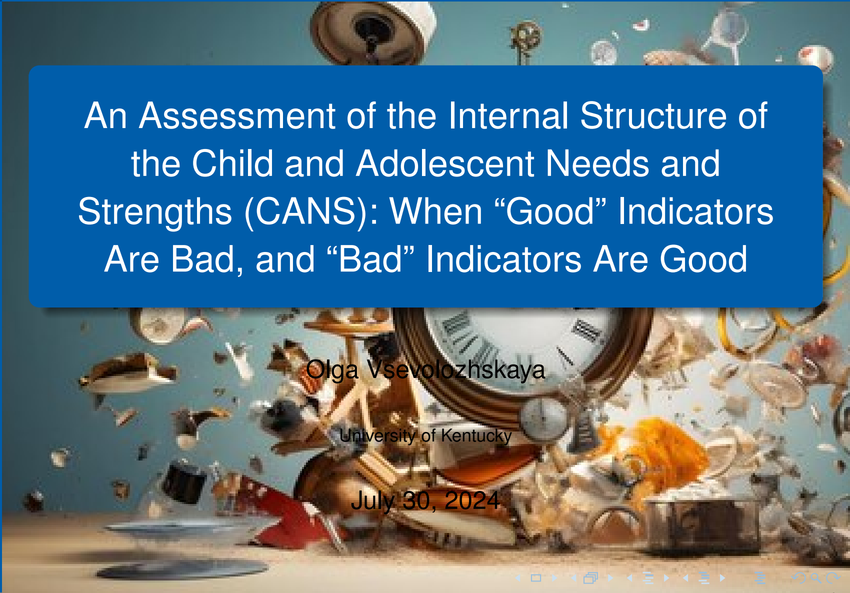

# An Assessment of the Internal Structure of the Child and Adolescent Needs and Strengths (CANS): When “Good” Indicators Are Bad, and “Bad” Indicators Are Good

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# An Assessment of the Internal Structure of the CANS

In a recently published article by Childs and colleagues, the authors carefully study the internal structure of the Child and Adolescent Needs and Strengths (CANS) to evaluate its validity. The summary of their findings **does not conclude a strong support for the internal structure of the CANS.**

- The authors question the ‘validity’ of the CANS (translation: number of domains should be equal to the number of latent factors)
- The authors question the ‘internal consistency’ of the CANS (translation: high positive correlation of items within a domain and low correlation of items between domains)

Other scholars have argued that understanding the validity properties of the CANS is necessary (e.g., Sokol et al., 2020; Brown et al., 2022). In research settings, the CANS domains are used as unobserved variables measured over time or to predict client outcomes. The use of CANS domains as latent variables (i.e., CANS items summed or weighted to create domains) requires confirmation of internal consistency (Bollen, 1984; Little et al., 1999). Additionally, Kraus et al. (2015) and Kraus (2017; 2020) draw attention to the large number of items used to measure each domain, specifically whether these items measure the same construct (i.e., need) and if the identified construct provides meaningful treatment information. In research that investigates these issues, Kisiel et al. (2018) found variations in the internal consistency across each of the CANS domains among a sample of 257 children and adolescents referred for community mental health services. Moreover, using a sample of over 45,000 CANS assessments, Cordell et al. (2016) found 10 clusters of needs, rather than the 6 clusters specified by the CANS framework. In a recent review of empirical studies assessing the psychometric properties of the CANS, Brown et al. (2022) emphasized the lack of existing research addressing the dimensionality and internal consistency of the tool.

**Figure:** Childs, K.K., Bryson, S.L., Soderstrom, M.F. and Reed, A., 2024. An Assessment of the Internal Structure of the Child and Adolescent Needs and Strengths (CANS) Using Two Samples of High-Risk Adolescents. *Children and Youth Services Review, 156, p.107365.*

# An Assessment of the Internal Structure of the CANS

The authors used Confirmatory Factor Analysis (CFA) to examine the internal structure of the CANS. Their tested model is depicted below.

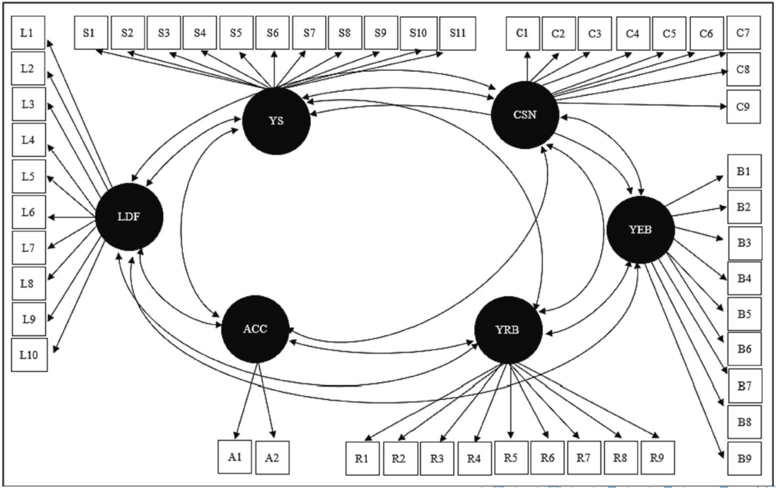



**Figure:** Figure 1 from Childs, et.al., (2024) outlining the internal structure of the CANS.

# An Assessment of the Internal Structure of the CANS



- *"[...] the hypothesized 6-factor structure of the CANS did not produce a strong fit of the model to the data, regardless of the sample analyzed."*
- *"[...] additional studies on the psychometric properties of the CANS, using both EFA and CFA, are necessary."*
- *"[...] identify the covariance structure of CANS items."*

**5. Discussion and conclusions**

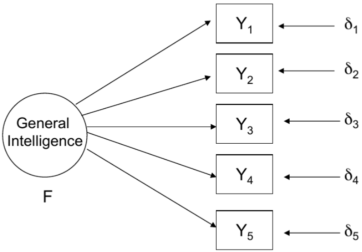
This study sought to examine the internal structure of the CANS. We compared a 6-factor CFA model (shown in Fig. 1) and Cronbach's alpha coefficients across two high-risk samples of youth ages 11 to 17. The findings demonstrated differences across samples in the prevalence and functionality of the items, levels of explained factor variance, and internal consistency. In summary, this study did not provide strong support for the CANS framework, as set forth in published CANS documentation (i.e., scoring sheets, training manuals). Tests of dimensionality (i.e., CFA) and internal consistency (α) across both samples suggested that the internal structure of the CANS framework is acceptable but not strong.

A closer look at the CANS items and correlations (see Appendix B) highlighted some potential reasons for our findings. For example, substance use is not correlated with many of the items included under the YEB domain. It is possible that substance use may better reflect the items under YRB, especially given the robust association found among delinquency, substance use, and other reckless behavior (Elliott et al., 2012; Mulvey et al., 2010). Similarly, oppositional and conduct problems are strong risk factors for many of the behaviors measured under YRB, show the highest item-factor relations compared to any other items under YEB, and are strongly associated with each other (Rowe et al., 2010). Thus, it is likely that these item-level associations contributed to the linear association among YRB and YEB, suggesting that YEB and YRB may be part of the same construct. It is important to note that our findings are not unique. For instance, Cordell et al. (2021) extracted "question clusters" of CANS items using a sample of over 45,000 CANS assessments. Ten clusters of items were identified, with each cluster containing items from multiple CANS domains. For instance, the

**Figure:** Childs, K.K., Bryson, S.L., Soderstrom, M.F. and Reed, A., 2024. An Assessment of the Internal Structure of the Child and Adolescent Needs and Strengths (CANS) Using Two Samples of High-Risk Adolescents. *Children and Youth Services Review, 156, p.107365.*

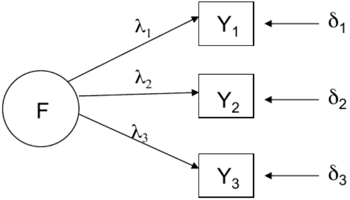
# Common Factors: A Very Brief Overview

- Why statistical variables are intercorrelated?
- Spearman's (1904) celebrated hypothesis was that mental tests were intercorrelated because they had a single general factor in common; if factor were partialed out, no correlations would remain.




- The generalization to multiple common factors by Spearman, Thurstone, Guttman and others remains a partial-correlation approach.

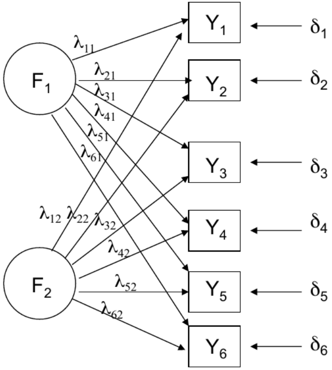
# One Common Factor Model




$$
\begin{aligned}
Y_1 &= \lambda_1 F + \delta_1 \\
Y_2 &= \lambda_2 F + \delta_2 \\
Y_3 &= \lambda_3 F + \delta_3 \\
cov(F, \delta_i) &= 0 \\
cov(\delta_i, \delta_i) &= 0 \\
cov(Y_i, Y_j \mid F) &= 0
\end{aligned}
$$

(translation: factorial causation; factors are independent of errors; errors are independent; given the factor, observed variables are independent of one another)

# Two Orthogonal Common Factors Model



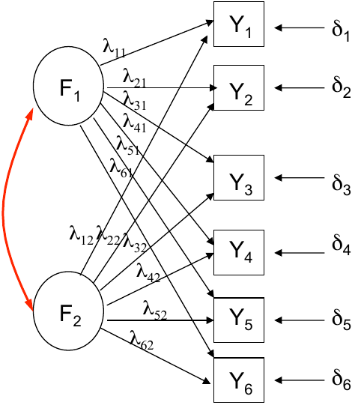

$$Y_1 = \lambda_{11}F_1 + \lambda_{12}F_2 + \delta_1$$
$$Y_2 = \lambda_{21}F_1 + \lambda_{22}F_2 + \delta_2$$
$$\vdots$$
$$Y_6 = \lambda_{61}F_1 + \lambda_{62}F_2 + \delta_6$$
$$cov(F_1, \delta_i) = cov(F_2, \delta_i) = 0$$
$$cov(\delta_i, \delta_i) = 0$$
$$cov(Y_i, Y_j \mid F_1, F_2) = 0$$
$$cov(F_1, F_2) = 0$$

$F_1$ and $F_2$ are common factors because they are shared by $\geq 2$ variables.

$F_1$ and $F_2$ are orthogonal (i.e., independent).

# Two Oblique Common Factors Model



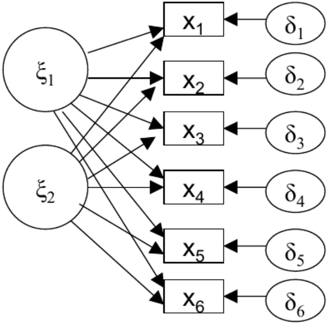



$$Y_1 = \lambda_{11}F_1 + \lambda_{12}F_2 + \delta_1$$
$$Y_2 = \lambda_{21}F_1 + \lambda_{22}F_2 + \delta_2$$
$$\vdots$$
$$Y_6 = \lambda_{61}F_1 + \lambda_{62}F_2 + \delta_6$$
$$cov(F_1, \delta_i) = cov(F_2, \delta_i) = 0$$
$$cov(\delta_i, \delta_i) = 0$$
$$cov(Y_i, Y_j \mid F_1, F_2) = 0$$
$$cov(F_1, F_2) \neq 0$$

$F_1$ and $F_2$ are common oblique (i.e., dependent) factors

# Exploratory Factor Analysis

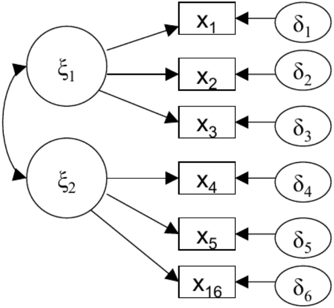





$$x_1 = \lambda_{11}\xi_1 + \lambda_{12}\xi_2 + \delta_1$$
$$x_2 = \lambda_{21}\xi_1 + \lambda_{22}\xi_2 + \delta_2$$
$$\vdots$$
$$x_6 = \lambda_{61}\xi_1 + \lambda_{62}\xi_2 + \delta_6$$
$$cov(\xi_1, \xi_2) \neq 0$$

$\xi_1$ and $\xi_2$ are common orthogonal factors

# Confirmatory Factor Analysis




$$x_1 = \lambda_{11}\xi_1 + 0 \cdot \xi_2 + \delta_1$$
$$x_2 = \lambda_{21}\xi_1 + 0 \cdot \xi_2 + \delta_2$$
$$\vdots$$
$$x_6 = 0 \cdot \xi_1 + \lambda_{62}\xi_2 + \delta_6$$
$$cov(\xi_1, \xi_2) \neq 0$$

$\xi_1$ and $\xi_2$ are non-common oblique factors

# Conclusion 1



When Childs and colleagues contrast their weak finding of 6 latent factors to 10 latent cluster found by Kate Cordell, they make inappropriate comparisons.

# Conclusion 2

Under common factor theory, implemented through exploratory factor analysis (more on this in next slides), multiple latent factors can jointly cause observations, so non-zero correlation of items from different domains are expected.

Question: Why is it a very bad idea to expect to find the same number of common factors as the number of domains in the CANS?

# Common Factor Analysis

Louis Guttman in his paper entitled "SOME NECESSARY CONDITIONS FOR COMMON-FACTOR ANALYSIS" (1954) writes:

1. *The Problem.* One of the fundamental problems of common-factor analysis—in the sense of Spearman, Thurstone, and others—is as follows. Given the Gramian matrix $R$ of the intercorrelations among $n$ observed variables, with each main diagonal element equal to unity. Let $U^2$ be an arbitrary diagonal matrix, with the $j$th main diagonal element denoted by $u_j^2$, subject to the restrictions that:

$$0 \leqq u_j^2 \leqq 1 \qquad (j = 1, 2, \cdots, n). \tag{1}$$

Let $G$ be the symmetric matrix defined by

$$G = R - U^2. \tag{2}$$

Find a $U^2$ which will leave $G$ Gramian but with the smallest possible rank.

# Common Factor Analysis

In common-factor theory, it is hypothesized that each $x_{ji}$, can be expressed as the sum of a common part,$c_{ji}$, and a unique part, $u_{ji}$:

$$x_{ji} = c_{ji} + u_{ji},$$

where the rank of $c_{ji}$ is of basic importance. Furthermore, the total variance of $x_{ji}$, taken as unity, is the sum of the variances of its common and unique parts:

$$\sigma^2_{c_j} + \sigma^2_{u_j} = 1.$$

The way common-factor theory "explains" the observed intercorrelations $\rho_{jk}$ is by means of its fundamental factor equation,

$$\rho_{jk} = E(c_{ji}, c_{ki}), \quad j \neq k.$$

# Common Factor Analysis



In matrix notation, common-factor theory assumes that an arbitrary rectangular matrix $\mathbf{S}$ of rank $r$ need to be factored in the form $\mathbf{FP}$, , where $\mathbf{F}$ has $r$ columns and $\mathbf{P}$ has $r$ rows.

$$\mathbf{S} = \mathbf{FP}$$

*Theorem 2.* If

$$R = \frac{1}{N} SS' = FF', \qquad (18)$$

*where* $\mathbf{S}$ *is of order* $\mathrm{n} \times \mathrm{N}$ *and of rank* $\mathbf{r}$, *and* $\mathbf{F}$ *is of order* $\mathrm{n} \times \mathbf{r}$ (*and of rank* $\mathbf{r}$), *then it is possible to determine a* $\mathbf{P}$ *of order* $\mathbf{r} \times \mathrm{N}$ *and such that*

$$\underline{S = FP.} \qquad (19)$$

*Furthermore, this* $\mathbf{P}$ *is uniquely determined, and it satisfies*

$$\frac{1}{N} PP' = I. \qquad (20)$$

# Common Factor Analysis



2. *The Unknown Communalities and Uniquenesses.* The $j$th diagonal element of a Gramian $G$ in (2) is called a "communality" of the $j$th observed variable, and is denoted by $h_j^2$. From (2) we have—considering the respective main diagonal elements of $G$ and $R$—

$$h_j^2 = 1 - u_j^2 \qquad (j = 1, 2, \cdots, n). \tag{3}$$

From (1)—which is actually a consequence of the restriction of $G$ to being Gramian—it must be that $0 \leqq h_j^2 \leqq 1$.

The quantity $u_j^2$ is called a "uniqueness" of the $j$th observed variable, when $G$ is Gramian.

Conventional empirical techniques for attempting to find a Gramian $G$ of minimum rank usually proceed as follows. A trial matrix $U^2$ is first used to define a $G$ as in (2), and one or more common-factors is "extracted"—usually by modifying the trial values of $U^2$ in the course of the computations—until a matrix is built up which differs from $R$ in the non-diagonal elements only by "small" residuals.

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# Common Factor Analysis



Olga Vsevolozhskaya

## How many latent orthogonal factors can one expect to find using Exploratory Factor Analysis?

Louis Guttman shows that it is *at least as many* as the number of eigenvalues greater than one of the empirical correlation matrix, $\mathbf{R} = \frac{1}{N}\mathbf{S}\mathbf{S}'$.

5. *The Three Lower Bounds.* Let $r$ be the (unknown) minimum rank possible for a Gramian $G$ in (2) for the given $R$. Let $s_1$ be the number of latent roots of $R$ which are greater than or equal to unity. Then we shall show that $s_1$ is necessarily a lower bound to $r$:

$$r \geqq s_1 \ . \qquad (6)$$

BUT all non-zero eigenvalues of item intercorrelations, $\mathbf{R} = \frac{1}{N}\mathbf{S}\mathbf{S}'$, are the same as non-zero eigenvalues of subject intercorrelations $\mathbf{S}'\mathbf{S}$!

# Conclusion 3

If you perform an exploratory factor analysis and expect to find the same number of orthogonal common factors as the number of domains (e.g., 6) then you implicitly assume that the number of latent children typologies in your population is also equal to the number of domains.

- We want the number of latent factors discovered through EFA be greater then the number of domains.
- The attempt to map each domain to an orthogonal latent factor is likely to be futile to begin with. Otherwise, it could only be used in a very specific population with a rigid small number of orthogonal latent typologies that equate exactly to the number of domains.
- The results are highly dependent on the empirical correlation matrix $\Rightarrow$ more items means more orthogonal latent factors.

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