# Examining the Factorial Structure of the T-CRS 2.1

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Melissa R. Weber<sup>1,2</sup>, Bohdan S. Lotyczewski<sup>1,2</sup>, Guillermo Montes<sup>1,2</sup>, A. Dirk Hightower<sup>1,2</sup>, and Marjorie Allan<sup>1,2</sup>

#### Abstract

The factor structure of the Teacher–Child Rating Scale (T-CRS 2.1) was examined using confirmatory factor analysis (CFA). A cross-sectional study was carried out on 68,497 children in prekindergarten through Grade 10. Item reduction was carried out based on modification indices, standardized residual covariance, and standardized factor loadings. A higher order model with a general super-ordinate factor fit the data well, and is consistent with the notion of a unidimensional non-cognitive set of learning-related skills. Model-based reliability estimates are provided.

#### Keywords

scale development/testing, measurement, factor analysis, elementary school, teachers, education professionals

Children's social-emotional and behavior problems have been shown to influence later school and social competence across diverse areas, including social functioning (Denham et al., 2003), psychological well-being (Meagher, Arnold, Doctoroff, Dobbs, & Fisher, 2009), and cognitive achievement (Rapport, Denney, Chung, & Hustace, 2001), and are also predictive of later school performance (Guzman et al., 2011; Moilanen, Shaw, & Maxwell, 2010). Although unaddressed social-emotional problems tend to become chronic, timely and well delivered intervention for students at risk for social-emotional and behavioral problems can alter a developmental trajectory toward more favorable outcomes that may otherwise have become more difficult and costly to address later on (Nation et al., 2003; Smith & Tyler, 2010).

Early intervention and treatment depend on timely identification of at risk students as problems begin to emerge. According to Romer and McIntosh (2005), only 2% of schools in the United States screen all children for behavioral or emotional problems, and when they do, methods are often haphazard, unreliable, and potentially invalid (Guzman et al., 2011; Kamphaus et al., 2007). Despite the availability of a number of psychometric instruments designed to detect children at risk for adjustment problems in the classroom setting, a major shortcoming of these instruments is the length of teacher time needed to complete the assessment. This barrier becomes

<sup>1</sup>University of Rochester, NY, USA

**Corresponding Author:** Melissa R. Weber, Children's Institute, Inc., 274 North Goodman Street, Suite D-103, Rochester, NY 14607, USA. Email: mreynoldsweber@childrensinstitute.net

<sup>&</sup>lt;sup>2</sup>Children's Institute, Inc., Rochester, NY, USA

especially salient as education professionals increasingly face competing demands and time constraints. The objective of this study was to assess the factor structure, internal consistency, and validity of the Teacher–Child Rating Scale (T-CRS) 2.1, a brief teacher-completed screening tool for school children at risk for school adjustment problems.

# Method

# The Instrument

The T-CRS 2.1 (Perkins & Hightower, 2002) is a revised version of the T-CRS 1.0 (Hightower et al., 1986) for measuring children's behavior in the classroom context, and was standardized on a nationally representative sample. It is a 32-item teacher-completed screening tool measuring four primary and eight secondary domains of social, behavioral, and academic competencies in the preschool through secondary school environment. Four positive and four negative items load on the following primary scales developed via exploratory factor analysis: task orientation (TAOR), behavior control (BC), assertiveness (A), and peer-social skills (PSOC). Teachers rate each item according to how much he or she agrees that the item describes the child on an ordinal 5-point scale ranging from 1 = strongly disagree to 5 = strongly agree. An overall total score and four subscale scores are generated.

TAOR assesses a child's ability to focus on school-related tasks. Items include adaptive skills such as "Functions well even with distractions" and problematic behaviors such as "Has difficulty following directions." BC assesses a child's skill in tolerating and adapting to his or her limitations, or to externally imposed limits. "Accepts imposed limits" and "Disruptive in class" are examples of items in this domain. A measures a child's interpersonal functioning and confidence in dealing with peers. Examples are "Defends own views under group pressure" and "Anxious, worried." PSOC measures a child's likeability among peers, and his or her ability to interact positively with peers. "Has many friends" and "Lacks social skills with peers" are examples from this domain.

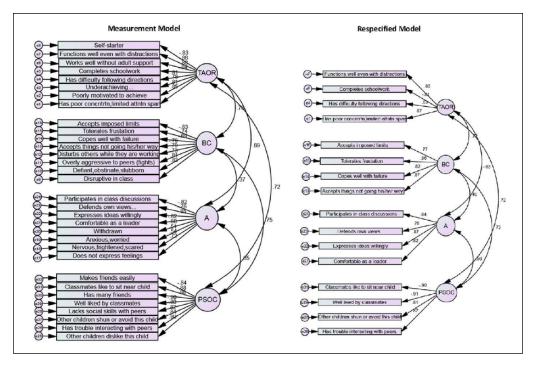
The T-CRS 2.1 revision was developed with input from teachers, psychologists, and measurement specialists to ensure that the items were pertinent to the measurement of social-emotional adjustment and covered the relevant content. The T-CRS 2.1 Examiner's Manual is the product of the most recent psychometric work on this instrument (Perkins & Hightower, 2002) and provides evidence of its technical adequacy. The purpose of the current study was to re-examine the psychometric properties of the T-CRS 2.1 using a large data set of over 68,000 records that were collected over 6 years from 2004-2005 to 2009-2010.

# Participants

Data were collected on 69,780 students (49% female) from 58 urban (50%), suburban (32%), and rural (19%) school districts across the United States. The data represent six cross-sectional cohorts of children in prekindergarten through Grade 10. Sixty-eight percent of the students were in kindergarten or first grade. These data were collected as part of routine universal screening activities associated with a school-based prevention program to support children identified as being at risk for school adjustment problems.

# Data Analytic Method

Exploratory factor analysis (EFA) has been used in many studies as an item reduction technique. However, EFA is most appropriate when researchers have few, if any, hypotheses about a scale's internal structure. In contrast, confirmatory factor analysis (CFA) is useful when researchers



**Figure 1.** Measurement model and re-specified model of the T-CRS 2.1 with standardized loadings tested in confirmatory factor analysis.

*Note.* T-CRS = Teacher–Child Rating Scale; TAOR = task orientation; BC = behavior control; A = assertiveness; PSOC = peer-social.

have clear hypotheses regarding the number of dimensions underlying its items, the links between specific items and specific factors, and the association between factors. CFA is used in this study because it accommodates a priori expectations (Byrne, 2010), and can be an iterative process in which a scale's hypothesized measurement model is evaluated, revised, and re-evaluated using a combination of statistical and conceptual justification. The goal was to eliminate problematic items from the model while maintaining the integrity of the overall construct.

Analysis of the data. Out of 69,780 records, 68,497 were missing zero or one score on any given subscale. These data were randomly split into initial and cross-validation samples of equal size. Subsample 1 was used to eliminate items from a correlated first-order model (Figure 1). Subsample 2 served to assess generalizability. Item reduction was carried out in Amos 19 based on the modification indices, standardized residual covariance, and standardized factor loadings. Following identification of a good fitting correlated model, we tested a higher order model with a general factor directly influencing the four group factors, and a bifactor model that allowed us to obtain omega coefficients: model-based reliability estimates (McDonald, 1999). Omega ( $\omega$ ) estimates the reliability of the general factor (total score) and is based on the proportion of total common variance explained. Omega hierarchical ( $\omega$ H) gives the proportion of variance in scale scores accounted for by a general factor. Omega subscale ( $\omega$ S) indicates the unique contribution of variance from the subscale factors.

A combination of statistical, practical, and theoretical criteria drove decisions regarding model fit (Byrne, 2010). Following the recommendations in Byrne (2010) and Hooper, Coughlan, and Mullen (2008), we examined both absolute and relative fit indices that are insensitive to sample

Model	Sample	n	$\chi^2\_SB$	Þ	CFI_SB	RMSEA_SB
Full T-CRS 2.1	I	32,526	93,763.983	<.001	.855	.079
Reduced T-CRS 2.1	I	32,526	12,351.189	<.001	.958	.062
Reduced T-CRS 2.1	2	32,933	12,035.063	<.001	.959	.061

Table 1. Global Fit Measures for the Full and Reduced T-CRS.

Note. Sample 1 represents the initial first half of the randomly split sample; Sample 2 represents the second half of the sample for cross-validation purposes. T-CRS = Teacher–Child Rating Scale;  $\chi^2$ \_SB = Satorra–Bentler adjusted chi-square; CFI\_SB = Satorra–Bentler adjusted comparative fit index; RMSEA\_SB = Satorra–Bentler adjusted root mean square error of approximation.

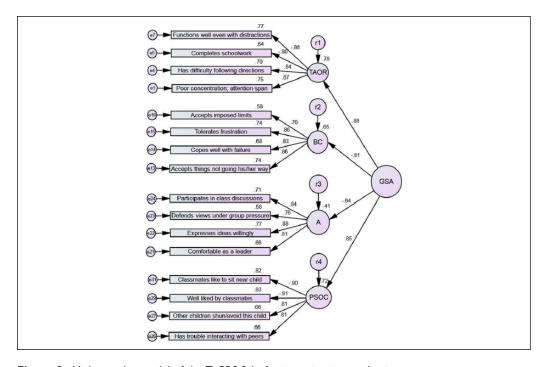
size including the root mean square error of approximation (RMSEA) and the comparative fit index (CFI). Absolute fit indices determine how well the a priori model fits the sample data, and relative fit indices determine how well the a priori model fits compared with the null model (McDonald & Ho, 2002). Cutoffs for model fit included an upper limit RMSEA value of .07 (Steiger, 2007) and lower limit CFI value of .95 (Hu & Bentler, 1999). Because our data are multivariate non-normally distributed, fit indices obtained via maximum likelihood estimation were adjusted using the Satorra–Bentler chi-square statistic in Stata 14, which incorporates a scaling correction when distributional assumptions are violated (Satorra & Bentler, 1994).

# **Results and Discussion**

A total of 16 items were iteratively deleted from the full T-CRS 2.1. All retained items remained on their original scale. The tested and re-specified correlated first-order models are presented in Figure 1. Model fit coefficients for each sample are reported in Table 1. The original T-CRS 2.1 factor structure did not yield a CFA with good fit (CFI = .86; RMSEA = .079). The reduced model met many requirements for acceptable fit. The RMSEA was .06 for both the initial and cross-validation sample. The CFI met the acceptable value of .96 for both samples indicating that the hypothesized model fits both the samples well.

The higher order model with a general factor named Global School Adjustment (GSA) indirectly affecting all items fit the data well (Figure 2) and was further supported by the modelbased reliability estimates shown in Table 2. A strong general factor explained 81% of the variance suggesting that it reliably summarizes the scores. This finding is consistent with the notion of a unidimensional non-cognitive learning-related set of skills and behaviors comprised of interpersonal and work-related skills (McClelland, Morrison, & Holmes, 2000). However, this also suggests that the interpretation of the subscales as precise indicators of unique constructs is extremely limited.

Classroom context and individual teacher rating style are integral factors contributing to the rating process. Many of the items that did not perform well were the negatively worded indicators of problematic behavior. For example, "Defiant, obstinate, stubborn" and "Withdrawn" and "Anxious, worried" performed poorly and were thus removed. The latter two also lack salient observable behaviors that may escape the classroom teacher's awareness. Ambiguity may explain the poor performance of other items, such as "self-starter." Overall, the remaining subset of items seem to be comprised of a set of interpersonal and work-related self-regulatory skills (McClelland et al., 2000) that are more readily observed in the classroom. Future studies will entail multigroup comparisons to test for measurement invariance across gender and grade level, as well as an indepth examination of the utility of the T-CRS 2.1 as a screening tool.



**Figure 2.** Higher order model of the T-CRS 2.1 after iterative item reduction. *Note.* Fit indexes for this model were as follows: Satorra–Bentler (SB) adjusted chi-square ( $\chi^2$ \_SB) = 412,732.66; SB adjusted comparative fit index (CFI\_SB) = .95; SB adjusted root mean square error of approximation (RMSEA\_SB) = .066. T-CRS = Teacher–Child Rating Scale; TAOR = task orientation; BC = behavior control; GSA = global school adjustment general factor; A = assertiveness; PSOC = peer-social.

Table 2. Standardized Factor Loadings and Reliability Coefficients (Omegas) of a Bifactor Model:						
General Factor and Four Subgroup Factors ( $n = 32,526$ ).						

		General	TAOR	BC	А	PSOC	3
TCRS5	Has difficulty following directions	-0.777	0.308				0.580
TCRS9	Functions well even with distractions	0.786	-0.378				0.457
TCRS25	Completes schoolwork	0.748	-0.279				0.567
TCRS29	CRS29 Has poor concentration attention		0.505				0.395
TCRS6 Accepts imposed limits		0.718		0.281			0.597
TCRS14 Tolerates frustration		0.675		0.542			0.355
TCRS22	Copes well with failure	0.626		0.565			0.378
TCRS30	Accepts things not going his or her way	0.669		0.541			0.376
TCRS3	Participates in classroom discussions	0.575			0.607		0.449
TCRSII Defends own views under group pressure		0.414			0.662		0.552
TCRS19 Expresses ideas willingly		0.529			0.707		0.313
TCRS27 Comfortable as a leader		0.552			0.593		0.575
TCRS12	Other children shun or avoid	-0.674				0.454	0.344
TCRS16	Classmates like to sit near child	0.754				-0.501	0.203
TCRS20	Has trouble interacting with peers	-0.734				0.349	0.478
TCRS32	Well-liked by classmates	0.747				-0.53 I	0.159
Omega ( $\omega$ ) and Omega subscale ( $\omega$ S)		0.995	0.49	0.69	0.78	0.71	
Omega hierarchical (ωH)		0.813					

Note. Negative factor loadings were reflected to express their absolute value prior to calculating the omega coefficients. T-CRS = Teacher–Child Rating Scale; TAOR = task orientation; BC = behavior control; A = assertiveness; PSOC = peer-social;  $\varepsilon$  = error variance.

#### **Declaration of Conflicting Interests**

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