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Article *in* Research on Social Work Practice · January 2012

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Research on Social Work Practice 2012 22: 77 originally published online 19 July 2011
DOI: 10.1177/1049731511415549

Research on Social Work Practice
22(1) 77-84

DOI: 10.1177/1049731511415549
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Confirmatory Factor Analysis of the Elementary School Success Profile for Teachers

Kristina C. Webber[1], Cynthia F. Rizo[1], and Natasha K. Bowen[1]

Abstract

Objectives: This study examines the factor structure and scale quality of data collected with the online Elementary School Success Profile (ESSP) for Teachers from a sample of teachers of 1,145 third through fifth graders. Methods: Confirmatory factor analysis (CFA) using Mplus and weighted least squares means and variances adjusted (WLSMV) estimation took into account the ordinal and clustered nature of the data. Models were tested on four random subsamples. Results using maximum likelihood (ML) estimation are presented for comparison. Results: A five-factor, first-order model demonstrated superior fit. Scores from the five scales demonstrated acceptable reliability. Conclusions: Results suggest the *ESSP for Teachers* provides school practitioners with quality data to guide intervention choices in schools. Implications for future research are discussed.

Keywords

education, children, teachers, factor analysis, validity study, internal consistency

Schools are a primary social context for children's academic and social–emotional development (Richman, Bowen, & Woolley, 2004; Roeser, Eccles, & Sameroff, 2000). Given the amount of time children spend in school, knowledge of student experiences in this domain can be vital to guiding efforts to support children's academic success, social and emotional development, and overall well-being. Students, parents, and teachers provide three unique perspectives on children's experiences in school. Each of these three perspectives has limitations, yet contributes a valuable and unique understanding of a child's experiences and behavior in school (Achenbach, McConaughy, & Howell, 1987; Campbell & Fiske, 1959; Pepler & Craig, 1998).

Teachers are generally considered an important, authoritative source of information about their students. Teachers' frequent and sustained interactions with students provide ample opportunity to observe children individually and in groups in the school context. This position affords a unique and valuable vantage point on children's social skills, academic and learning behaviors, internalizing and externalizing behaviors, and peer interactions in the classroom and other school settings (Bennett, Gottesman, Rock, & Cerullo, 1993; Cullerton-Sen & Crick, 2005; Pellegrini & Bartini, 2000). Without the inclusion of teachers as reporters, significant information related to children's well-being may be missed. For example, Cullerton-Sen and Crick (2005) found that teacher-report variables explained variance in poor student behavior outcomes, above and beyond variance explained by peer and self-reports. Furthermore, teacher reports predicted poor outcomes as well as, or somewhat better than, parent reports (Cullerton-Sen & Crick, 2005).

Because of teachers' distinct and valuable perspective, assessments that rely on teacher judgments of students are used widely in both research and practice settings. Teacher ratings are frequently used as the sole measure of children's social–emotional, intellectual, or behavioral development in studies of school-based intervention programs. School social workers, psychologists, counselors, mental health professionals, and other school-based practitioners also rely on teachers' perceptions of a child's social and academic experiences to inform prevention and intervention decisions. For example, teacher judgments of student behavior play a key role in identifying students for academic interventions (e.g., gifted or special education programs) and mental health services (Bennett et al., 1993). Teacher ratings are also used to garner information about students' available support systems, including peer relationships and parent/guardian school involvement (Cullerton-Sen & Crick, 2005). Although the need for teacher-report data on students is clear, exigencies of the school setting dictate that assessment tools for teachers be feasible to use as well as collect psychometrically sound data.

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The Elementary School Success Profile

The current study reports on the factor structure and reliability of the *Elementary School Success Profile (ESSP) for Teachers* (Bowen, 2006; Bowen & Powers, 2005; Woolley, Bowen, & Bowen, 2004). The *ESSP for Teachers* is one component of a comprehensive, multiple-source online assessment tool designed to help school-based practitioners identify social–environmental influences that promote or impede school success among third through fifth grade students (Bowen, 2006). The ESSP is based on the School Success Profile (SSP; Bowen, Richman, & Bowen, 2002; Bowen, Rose, & Bowen, 2005), a self-report social–environmental assessment for middle and high school students.

The ESSP collects data from students, parents, and teachers. Together, the three components of the ESSP assess 28 developmentally relevant dimensions across eight domains: neighborhood, family, school, friends, parent education involvement, health and well-being, social behavior at home and school, and school performance. Sources of data within domains overlap when appropriate, providing multiple perspectives (e.g., teachers and parents) on the same social–environmental factor (e.g., parent education involvement) or child characteristic (e.g., social behavior). This combination provides a fuller, more contextualized understanding of risks and strengths to better inform intervention selection and delivery. By collecting this information, school practitioners are broadening their search for the potent influences on student social and academic behavior that are most amenable to intervention (Bowen, Lee, & Weller, 2007; Silverman & Saavedra, 2004). An overview of each of the domains and dimensions assessed with the ESSP is available elsewhere (Bowen, Bowen, & Woolley, 2004; http://www.schoolsuccessonline.com).

The ESSP has demonstrated several characteristics of a good assessment, including practice-related validity (Bowen, 2006; Bowen & Powers, 2005), score performance of the child report (Bowen, 2006, 2010) and family report (Wegmann, Thompson, & Bowen, 2011), and feasibility for use in school settings (Bowen & Powers, 2005). Establishing the quality of data collected with the teacher report, therefore, is the next step in validating the ESSP as a whole. The purpose of the current study was to test the factor structure and scale quality of data collected with the *ESSP for Teachers*, with two specific goals in mind. First, although this study focuses solely on the teacher component, our analysis builds on recent findings regarding the factor structure of the *ESSP for Families* (Wegmann et al., 2011) with the goal of keeping the two components consistent to allow for cross-informant comparisons. Second, we hoped to reduce the length of the assessment, while maintaining reliability and the factor structure of the measure, to increase its feasibility for use in schools.

In the following sections, we present a confirmatory factor analysis (CFA) of *ESSP for Teachers* data and the reliabilities of the resultant scales. In addition to presenting findings related to the *ESSP for Teachers*, we address the challenges posed by ordinal and nested data with missing values by using best practices to evaluate the psychometric properties of the instrument.

Method

Sample

The ESSP data were collected for 1,251 third through fifth grade students attending 13 low-performing schools in a south-eastern state. Responses to *ESSP for Teachers* items were available for 91% ($n = 1{,}145$) of the 1,251 students represented in the data from the 13 schools; these students were the analyzed sample. Each of the 13 schools took part in one of four ESSP projects operating during the 2008–2009 school year. Located in 4 school districts scattered throughout the state, the 13 schools represented both rural and urban regions and were diverse in terms of racial/ethnic composition and availability of community resources. Recruitment of participants varied across the four school districts. Five schools, representing two economically depressed rural communities, targeted all third through fifth grade students for assessment. In another community, four elementary schools selected students randomly from among their low-achieving third, fourth, and fifth graders. The remaining community targeted all fourth grade students in four schools. All human subjects and data use procedures were approved by the Institutional Review Board of the University of North Carolina at Chapel Hill.

Two of the sources of ESSP data—teachers and parents—provide child demographic data. Teachers provide students' grade level and parents provide gender, race/ethnicity, and free/reduced lunch program participation. Due to lower rates of survey participation among parents as compared to teachers, data on the parent-reported characteristics were available for only 57% of the study sample. According to teacher report, the sample consisted of students in third (35%), fourth (43%), and fifth grade (22%). According to parent report, over half of the students (55%) were female and 45% were male. In all 48% of parents reported their child's race/ethnicity as White; with 37% indicating African American, 6.7% Hispanic, 5.2% multiracial, 2.3% Asian, and 0.8% Native American race/ethnicity. The remainder (0.5%) reported their child's race/ethnicity as "other." Over half of the parents (56%) reported that their children received free or reduced price meals at school, indicating limited family financial resources. Teacher reports indicated 38% of students were performing below grade level in reading and 40% of students were performing below grade level in mathematics.

Measures

The initial version of the *ESSP for Teachers* consisted of 33 items exploring teachers' perceptions of the social and learning behaviors of students at school and the school involvement of parents. As described earlier, the parent and teacher forms of the ESSP include several parallel scales, where parents and teachers respond to similar items, albeit regarding different settings. Given our desire to keep the various components of the

Table 1. ESSP for Teachers—Social and Learning Behavior Items Submitted for CFA

Factor	Summary of Content
Is sociable with other children	Three items assessing how often the child plays with others and is accepted by/plays with other well-behaved children
Uses good social skills	Three items assessing how often the child thinks before acting, calms down when excited, and controls temper
Interacts peacefully	Four items assessing how often the child fights, harms others, plays aggressively, and hits on purpose
Tries to be a good learner	Eight items assessing how often the child completes assignments, learns up to ability, is eager to learn, stays on task, concentrates, works hard, pays attention, and is self-reliant
Parent involvement at school	Six items assessing how the caregiver attends parent–teacher conferences, volunteers at the school or classroom, attends school events, contacts school staff about the child, attends information sessions at the school, and goes to parent–teacher association (PTA) meetings

Note. CFA = confirmatory factor analysis; PTA = parent–teacher association.

ESSP package consistent, nine items were eliminated from the *ESSP for Teachers* prior to our analysis based on a recent validation study of the *ESSP for Families* (Wegmann et al., 2011). Therefore, only 24 of the 33 original items from the *ESSP for Teachers* were used in the current analysis. As presented in Table 1, the 24 items submitted for analysis were hypothesized to represent five dimensions. Items on four dimensions were derived from the Carolina Child Checklist (CCC; Macgowan, Nash, & Fraser, 2002); the CCC is an adaptation of the Social Health Profile (SHP) and the Teacher Observation of Classroom Adaptation-Revised (TOCA-R). These four scales are called Interacts Peacefully, Is Sociable with Other Children, Uses Good Social Skills, and Tries to Be a Good Learner. Items on these four scales are assessed with six ordinal response options (*Never*, *Rarely*, *Sometimes*, *Often*, *Very Often*, and *Always*). Items on the remaining dimension, Parent Involvement at School, were based on a scale from the SSP (Bowen et al., 2005) and additional theoretically salient aspects of parent engagement. The parent involvement items are assessed with four ordinal response options (*Never*, *Sometimes*, *Often*, and *Always*).

Analysis Procedures

Preliminary analysis identified several important characteristics of the ESSP data in need of special attention. These included the presence of ordinal variables, missing data, nonnormality, and nesting (i.e., individual students clustered within the 13 schools). Mplus version 4.21 (Muthén & Muthén, 2007) was used based on its ability to adequately handle the characteristics of the data. Weighted least squares means and variances adjusted (WLSMV) is a robust estimation method capable of providing accurate estimates and standard errors in situations with ordinal data (Flora & Curran, 2004). The WLSMV in Mplus uses a polychoric correlation matrix and an associated weight matrix (Muthén & Muthén, 1998–2007) instead of the Pearson's correlation matrix used by other estimators, such as maximum likelihood (ML). The polychoric correlation matrix addresses the ordinal and nonnormal distribution characteristics of the data by assuming underlying theoretical normal distributions of categorical variables with thresholds derived from bivariate distributions of the original variables. Although rates of missing data on the variables of interest were low (ranging from 0.8 to 3.6%), the full information maximum likelihood (FIML) procedure available in Mplus was used to handle missing data. The FIML procedure, which allows all available information to be used in the analyses without deleting cases, avoids the biased parameter estimates likely to occur with other common approaches to handling missing values, such as case deletion or mean substitution (Enders & Bandalos, 2001; Schafer & Graham, 2002). Additional information regarding the Mplus syntax, the polychoric correlation matrix, and the associated weight matrix used in these analyses is available from the first author upon request.

Comparison of analysis methods. To examine the influence of the clustering and measurement-level characteristics of the ESSP data, the Mplus analyses described above were repeated using the AMOS version 16.0 software package (Arbuckle, 2007; Byrne, 2010). The default procedures in AMOS are commonly used for CFA studies in the social sciences. Our Mplus and AMOS analyses differed in three key areas. First, the AMOS analysis employed the more commonly used ML estimation method, which does not take into account the ordinal nature of the ESSP data. Second, the AMOS analysis did not account for the clustering of data by school. Third, although both Mplus and AMOS employ a full-information procedure to handle missing data, the procedure used by AMOS precludes generation of modification indices.

Model specification. As described in the Measures, the factor structure of the initial model was specified based on existing measures (i.e., CCC and SSP) and a concurrent factor analysis study of the *ESSP for Families* (Wegmann et al., 2011). To set a metric for each factor, unit loading identification constraints were imposed (Kline, 2005); that is, the unstandardized coefficient of one item per latent variable was fixed equal to one. Figure 1 presents the initial model, consisting of 5 factors and 24 indicators.

Calibration and validation subsamples. The relatively large size of the sample allowed us to follow the recommended CFA procedure of using independent samples for purposes of calibration and validation, particularly when making modifications to an initially specified model (de Vet, Adèr, Terwee, & Pouwer, 2005; Kline, 2005). The study data were divided into four random subsamples. The first subsample ($n = 300$) served

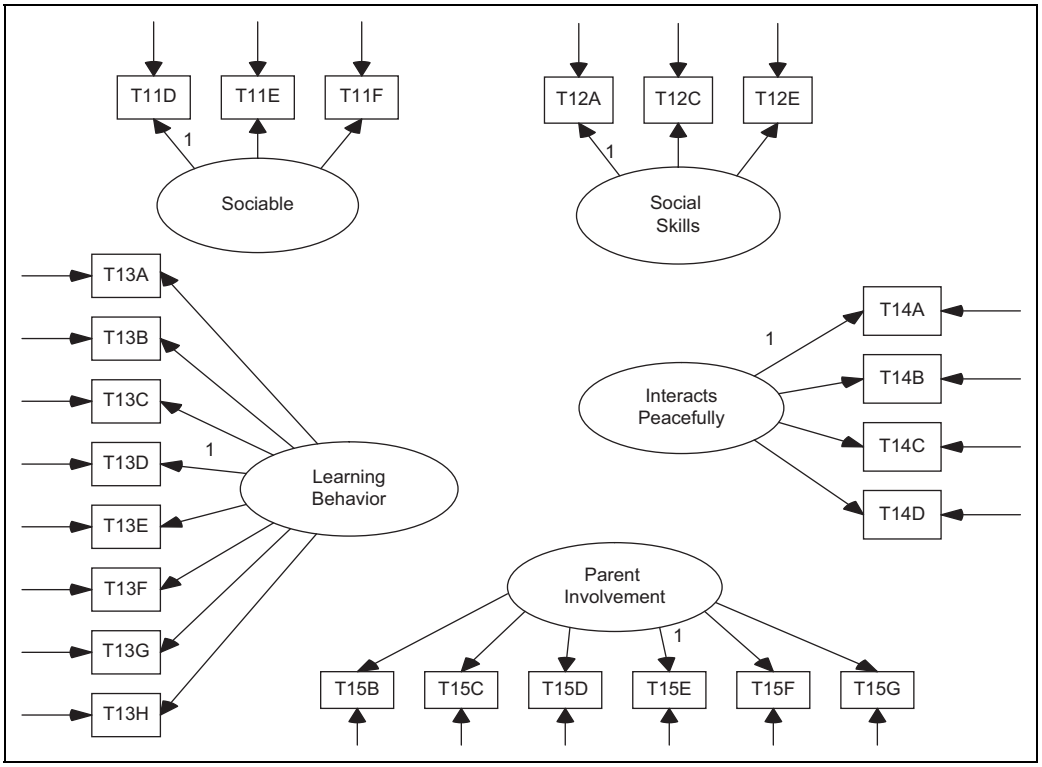

Figure 1. Initial model of 24 items from the *ESSP for Teachers*.

as the calibration sample. The remaining quarters (validation 1, $n = 273$; validation 2, $n = 288$; validation 3, $n = 284$) were used to validate the results of the calibration analysis. Chi-square tests conducted in SPSS version 17.0 (SPSS, 2009) indicated the four subsamples were not significantly different on important student characteristics (i.e., gender, race/ethnicity, grade level, free/reduced lunch status, academic performance in mathematics and reading).

Model fit. Assessment of model quality was based on the evaluation of parameter estimates (e.g., factor loadings, variances) and fit indices. In assessing the factor structure of a model, we examined whether (a) indicators primarily loaded onto specified factors, and (b) indicators representing the same factor evidenced similar loadings. We sought high and statistically significant factor loadings and the absence of high double loadings and Heywood cases (i.e., cases with negative error variance or a standardized factor loading greater than one). As recommended in the factor analysis literature, a combination of fit indices was used to comprehensively evaluate model fit and corroborate results (Hoyle, 1995; Thompson, 2004). The following fit indices were used: Satorra Bentler Scaled χ^2 (SB χ^2; χ^2 adapted for WLSMV by Mplus), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Weighted Root Mean-Square Residual (WRMR). Despite the known limitations of the χ^2 statistic (i.e., sensitivity to sample size), a nonsignificant SB χ^2 was sought (Muthén & Muthén, 2007). CFI and TLI values exceeding .95 were considered desirable and indicative of good model fit (Hu & Bentler, 1999). The RMSEA values between .05 and .08 were considered indicative of reasonable error of approximation, whereas values less than or equal to .05 were considered suggestive of close model fit to the data (Browne & Cudeck, 1992). Values below .90 were sought for the WRMR, a fit index provided by Mplus when WLSMV estimation is used (Muthén & Muthén, 1998–2007).

Reliability. Cronbach's α, obtained in SPSS for Windows version 17.0 (SPSS, 2009), was used to assess the internal consistency of scales resulting from the final CFA model. Standard cutoff values of α were used, with $\alpha \geq .70$ indicating adequate reliability, $\alpha \geq .80$ indicating very good reliability, and $\alpha \geq .90$ indicating excellent reliability (Kline, 2005). High reliabilities were desired because the ESSP is intended for use in practice settings (Nunnally, 1978).

Although Cronbach's α is the most commonly reported measure of internal consistency (Graham, 2006), it is important to acknowledge the limitations of this method. Specifically, coefficient α can underestimate the true reliability of the data, when assumptions of the method are violated (e.g., τ-equivalence of the individual items of a latent variable; Raykov, 2009). Our preliminary reliability analysis using latent variable modeling techniques (Graham, 2006; Raykov, 2001, 2009) suggest our scales violate the restrictive assumptions of coefficient α (e.g., τ-equivalence), resulting in reliability estimates that are lower (α's ranging from .88 to .98) than estimates based on methods with less restrictive assumptions (i.e., congeneric model; ρ's ranging from .96 to .99). As such, the

Table 2. CFA Results for Model Fit

Model	*n*	Fit Index				
		χ^2 (*p*)	TLI	CFI	RMSEA	WRMR
Initial (calibration sample)	300	18.79 (.00)	0.998	0.998	0.084	0.892
Final (calibration sample)	300	9.99 (.12)	0.999	0.999	0.047	0.568
Final (validation sample 1)	273	16.13 (.04)	0.998	0.997	0.061	0.562
Final (validation sample 2)	288	Theta matrix not positive definite				
Final (validation sample 3)	284	Theta matrix not positive definite				
Final (ML estimation in AMOS; calibration sample)	300	191.32 (.00)	0.984	0.978	0.051	—

Note. χ^2 = Satorra Bentler scaled chi-square (for all models except the ML estimation in AMOS, which uses an unadjusted chi-square); AMOS = analysis of moment structures; CFA = confirmatory factor analysis; CFI = comparative fit index; ML = maximum likelihood; RMSEA = root mean square error of approximation; TLI = Tucker–Lewis Index; WRMR = weighted root mean square residual (not available in AMOS).
Recommended cutoffs: $p > .05$ (χ^2); $\geq$.95 (TLI & CFI); <.05–.08 (RMSEA); $\leq$.90 (WRMR).

Cronbach's αs we report should be considered lower bound estimates of reliability (Graham, 2006).

Results

CFA Calibration

Figure 1 presents the initial model involving 24 measured variables and 5 factors. The CFA results indicate all standardized regression weights were significant and above the specified .40 cutoff (ranging from .83 to .99). Squared multiple correlations ranged from .69 to .98, indicating that a high percentage of the variance in each observed variable was explained by the model. As presented in Table 2, only three of the five preestablished fit criteria were met (TLI, CFI, WRMR). At this level of fit, theoretically and statistically justifiable modifications to the model should be considered (Hu & Bentler, 1999). Modification options included examination of the following: (a) modification indices, (b) residuals, (c) parameter estimates, and (d) explained variance. Taken together, sources of model information suggested the deletion of items for three of the five hypothesized factors. Although item deletion is an extreme modification procedure, evidence of excessive redundancy of items and our interest in increasing the feasibility of data collection from teachers suggested it was appropriate. In addition, few other options exist for managing relatively low (e.g., <.20) but statistically significant cross-loadings of items that are detrimental to model fit (Kline, 2005). Seven items were deleted, reducing the number of indicators in the initial model from 24 to 17. Additionally, one correlated error term was allowed between two items on the *Tries to be a Good Learner* scale. Both items are related to students' focus and attention in the classroom. The final five-factor model, presented in Figure 2, demonstrated good fit in the calibration sample ($n = 300$) according to all preestablished fit criteria, including a nonsignificant SB χ^2 value (see Table 2). The standardized regression weights for the final model ranged from .83 to .99 and the squared multiple correlations ranged from .69 to .98. As shown in Table 3, the names of two scales were changed to better reflect the nature of retained items.

CFA Validation

The final model was tested on three validation samples. Using the first validation sample, the model demonstrated good to reasonable fit based on four of the five preestablished fit indices (CFI, TLI, RMSEA, WRMR; see Table 2). The SB χ^2 value was statistically significant, although it approached nonsignificance. Testing of the model with the two remaining validation samples resulted in inadmissible solutions. Specifically, a nonpositive definite θ matrix because of negative error variances rendered results uninterpretable. High multicollinearity combined with use of the WLSMV estimation method may explain these findings. High multicollinearity in data can be further accentuated by the polychoric correlation matrix used by the WSLMV estimation method (Bollen, 1989) leading to statistically unstable results and resulting in nonpositive definite solutions more often than other estimation methods such as ML (Kline, 2005).

Methods Comparison: WLSMV Versus ML

As an additional means of model validation, we compared two CFA procedures: (a) WLSMV estimation using Mplus and (b) ML estimation using AMOS. With the exception of a significant χ^2 value (191.319; $p < .001$), ML estimation of the final model using the calibration sample resulted in good model fit: CFI = .984; TLI = .978; RMSEA = .051 (the WRMR fit index is not available in AMOS). This comparison strengthens our confidence in the results because we were able to achieve reasonable model fit using two different estimation methods.

Reliability Estimates

Internal consistency reliability was assessed for the five scales on the *ESSP for Teachers* based on the items retained in the final model. Cronbach's α coefficients were very good to excellent for all scales, ranging from .88 to .98 (Kline, 2005). As displayed in Table 3, reliability coefficients did not change substantially from the original to reduced instrument.

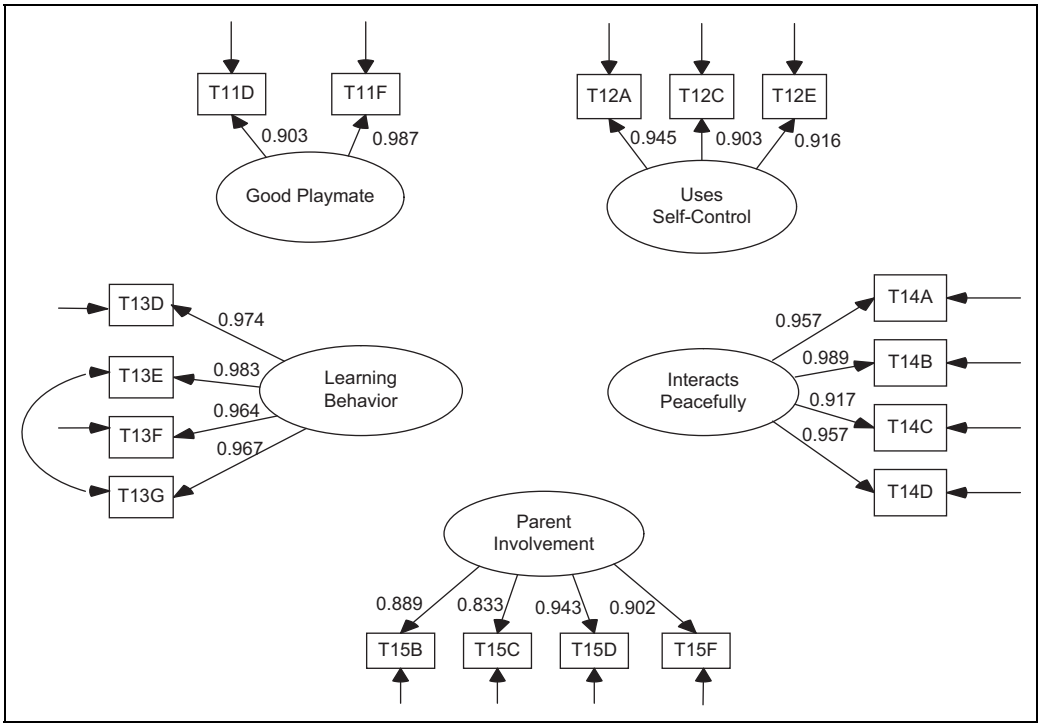

Figure 2. Final model with standardized loadings for 17 items from the *ESSP for Teachers*.

Table 3. Scale Names and Reliability Estimates for Original and Final Versions of the ESSP for Teachers

Original ESSP for Teachers (33 items)		Revised ESSP for Teachers (17 items)	
Scale Name	α	Scale Name	α
Is sociable with other children	.949	Is a good playmate	.907
Uses good social skills	.952	Uses self-control	.917
Tries to be a good learner	.980	Tries to be a good learner	.978
Interacts peacefully	.945	Interacts peacefully	.945
Parent involvement at school	.915	Parent involvement at school	.883

Note. ESSP = Elementary School Success Profile.

Discussion and Applications to Social Work

This study represents the first examination of the underlying factor structure of the *ESSP for Teachers*. We conducted a CFA of teacher report data on 24 indicators of five dimensions of parent involvement and child school behavior. Estimation methods available in Mplus 4.21 were used to strengthen the rigor of our study because these methods accommodate nested, nonnormal, and ordinal data with missing values. Furthermore, we validated our model using separate random samples and an alternative estimation procedure. Results suggest that with few modifications, the theoretical model structure of the *ESSP for Teachers* fit the data well. Specifically, the calibration sample and one of our three validation samples evidenced good CFA model fit based on various fit indices. Good model fit was also suggested by the two different estimation methods employed (i.e., ML and WLSMV).

The final model resulted in 17 items loading on five scales: Good Playmate, Self-Control, Learning Behavior, Interacts Peacefully, and Parent Involvement. Items were deleted primarily due to cross-loadings that were detrimental to fit, in spite of relatively low magnitudes. Internal consistency coefficients remained high for the reduced scales. Shortening the teacher-report scales increases the feasibility of the online ESSP in the school setting. Prior to this study, it took teachers about 7 min to complete the ESSP for each student. The shortened version should require, on average, 5 min or less.

A unique contribution of the ESSP is that it examines children in the school context from various perspectives—teacher, parent, and student. The current study found that the factor structure of behavioral and parent involvement items on the *ESSP for Teachers* closely parallels that of the *ESSP for Families* (Wegmann et al., 2011), further strengthening the assessment package as a whole. Parents and teachers each contribute a valuable and unique understanding of a child's experiences and behavior in school. Agreement and disagreement in the perspectives of teachers and parents can be used to inform the

nature, target, and scope of efforts to support children's academic success, social and emotional development, and overall well-being, while making the most effective use of schools' limited resources.

Establishment of factor structure and high reliability estimates point to evidence of scale quality. Positive findings on the psychometric properties of the *ESSP for Teachers* lends further support to the overall quality of the ESSP as a multisource tool to help school staff identify social–environmental influences that promote or impede students' school success. In conjunction with prior studies of the ESSP, the current study should increase practitioners' confidence in the ESSP as an efficient, valid, and valuable practice tool in schools.

Strengths of the current study are directly related to the diversity of the sample and the use of rigorous methods. Our sample was of adequate size to meet CFA requirements and represented a diverse group of children (e.g., gender, race/ethnicity, grade level, academic level, participation in free/reduced lunch program). Further, the use of Mplus to analyze our hierarchical, nonnormal, and ordinal data with missing values enabled us to take full advantage of the available data. The current study's approach to address issues of ordinal and hierarchical data is an important contribution, given that social work research often does not adequately handle restrictions inherent in the nature of the data. In addition to employing rigorous statistical methods, the study's use of validation samples and alternative estimation approaches to examine model fit adds credence that findings are not based on chance.

The primary limitation of the current study is the inability to replicate results of the final model with all three validation samples. Despite successful replication with one validation sample, two other validation samples resulted in inadmissible solutions due to cases of negative error variance. Although our analyses were guided by best practices (e.g., use of WLSMV), one trade-off to using the most appropriate estimation method is the increased likelihood of inadmissible or unstable solutions, especially in cases of high multicollinearity (Kline, 2005). Although our replication using ML estimation in AMOS validated our model, caution must be taken in interpreting the study's findings. A second limitation of the study is that we did not obtain demographic information about the teachers who completed the assessment. It is possible that the instrument performs differently across different teacher populations, such as teachers of diverse racial/ethnic groups or teachers with different levels of experience.

Although this study provides further evidence of the validity of the ESSP, additional work is warranted. Given that two of our validation samples resulted in inadmissible solutions, future research is needed to validate the factor structure of the *ESSP for Teachers* with additional samples. Multiple group analysis should be used to examine the invariance of the factor structure across different teacher groups and across schools serving different student populations. In addition to examining the stability of constructs across populations, future work should attend to the stability of constructs over time. Test–retest reliability needs to be evaluated in the absence of efforts to intervene in dimensions assessed with the *ESSP for Teachers.* As a practice tool designed to help school staff identify potential intervention targets, the ESSP is also designed to be a tool to evaluate change on measured dimensions. Therefore, in addition to examining stability of scores in the absence of change, future research should examine the sensitivity of ESSP scores to true change.

Authors' Note

The ESSP is based on the School Success Profile (SSP), which was developed by Gary L. Bowen and Jack M. Richman. The authors have the sole responsibility for the content of this article.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research and/or authorship of this article: The ESSP has been developed in collaboration with Flying Bridge Technologies with grants from the National Institute on Drug Abuse (1 R42 DA13865-012, 3 R41 DA13865-01S1, 2 R42 DA013865-02, 1 R43 DA020217-01, and 2 R44 DA020217-02); grants to the third author from the Strowd Roses and Triangle Community Foundations; the University of North Carolina at Chapel Hill (UNC); and Jane A. Pfouts and Armfield-Reeves Innovation grants from the School of Social Work, UNC.

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