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Conflict, Closeness, and Academic Skills: A Longitudinal Examination of the Teacher–Student Relationship

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Abstract. The longitudinal relations between teacher–student relationship quality (TSRQ) and student achievement were examined to determine the directional associations between the quality of teacher-rated closeness and conflict with students, and measured math and reading achievement in a large, multisite sample of U.S. youth at first, third, and fifth grade. A longitudinal confirmatory factor analysis model of panel data was employed. After testing longitudinal factorial invariance across time, we tested heterogeneity in the factor variances and differences in the latent means. Math and reading achievement had longitudinal reciprocal relations. Math achievement explained small differences in subsequent teacher-rated closeness after controlling for previous levels of math achievement and teacher-rated closeness. Teacher-rated conflict served as a small but significant predictor of subsequent math achievement across measured time points but previous teacher-rated closeness did not explain subsequent reading or math achievement at any time point. Teacher-rated conflict was relatively stable across grades, whereas teacher-rated closeness varied from first to third grade. Reading and math achievement were highly stable predictors of future achievement. The findings suggested that in a lower-risk sample, measures of TSRQ and achievement may serve as predictors or outcomes and directionality of effects should not be assumed in advance.

Supportive teacher–student relationships are a critical factor in creating and maintaining a sense of school belonging that encourages positive academic and behavioral outcomes (Anderman & Anderman, 1999; Birch & Ladd, 1997; Gest, Welsh, & Domitrovich, 2005; Wentzel, 1997). Grounded in attachment theory (Ainsworth & Bowlby, 1991), the importance of early relationships in building children's working models of the world and subsequent relationships with others is emphasized. While initial work in attachment theory focused on mother–child relationships, the teacher–student relationship has been investigated with the emerging view that a caring and supportive teacher can make similar, meaningful impacts in shaping youth outcomes (Bretherton, 1992; Hughes, Cavell, & Willson, 2001; Sabol & Pianta, 2012). The teacher–student relationship is typically viewed as consisting of two primary dimensions: Closeness and Conflict. Closeness represents the warmth and positive affect between the teacher and the child and the child's comfort in approaching the

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teacher, whereas Conflict refers to the negativity or lack of dyadic rapport (Ladd & Burgess, 2001). Consequently, research in public schools has increasingly focused on the role of supportive relationships with teachers as a salient variable related to student outcomes (Eccles et al., 1993; Skinner & Belmont, 1993; Skinner, Zimmer-Gembeck, & Connell, 1998). This focus is understandable, as variables that typically demonstrate the strongest relationships with student achievement (e.g., socioeconomic status, school mobility) are often very difficult to manipulate, and relationships with classroom teachers represent a logical and malleable variable of investigation (Roorda, Koomen, Spilt, & Oort, 2011).

Although some researchers have focused on the improvement of teacher–student relationship quality (TSRQ)[1] as an intervention target (Murray & Malmgren, 2005), investigations of TSRQ are often cross-sectional by design (Decker, Dona, & Christenson, 2007; Mantzicopoulos & Neuharth-Pritchett, 2003; Murray, Murray, & Waas, 2008; Rey, Smith, Yoon, Somers, & Barnett, 2007). The use of a cross-sectional design has the potential to weaken conclusion validity when directionality is implied. In order to address this limitation, longitudinal studies have been employed to assess for directionality of TSRQ, achievement, and related constructs with teacher–student relationship serving as either an independent or dependent variable (Rudasill, Reio, Stipanovic, & Taylor, 2010). Four models may serve to explain the nature of the relations between achievement and teacher–student relationships. In the first, unidirectional pathways from teacher–student relationships to later achievement are present. In the second, unidirectional pathways from achievement to later teacher–student relationships explain the relations. In the third, a bidirectional model in which both unidirectional associations from earlier teacher–student relationships to later student achievement and earlier achievement to later teacher–student relationships are present. Finally, a fourth model is present in which relational and achievement constructs are correlated with each other at a given time point and results gleaned from predictive analysis are simply artifacts of these within-time correlations.

TEACHER–STUDENT RELATIONSHIP QUALITY PREDICTS ACHIEVEMENT

Theoretically, models of TSRQ predicting achievement are supported by work on creating caring school communities (Battistich, Solomon, Watson, & Schaps, 1997). Citing multisite longitudinal survey data, the authors posited that classrooms in which students feel cared for and respected (a central component of positive TSRQ) will result in more engaged learners. Hamre and Pianta (2001) bolstered this theoretical model by using measures of TSRQ collected at kindergarten to predict academic and disciplinary outcomes at eighth grade for a sample of 179 children (60% European American, 40% African American). Additionally, Hughes and Kwok (2007) employed latent variable structural equation modeling (SEM) to investigate the role of TSRQ, parent–teacher relationship quality (PTRQ), and student engagement on standardized achievement measures in a sample of 443 lower achieving, diverse students. Their use of latent variable SEM allowed them to examine direct and indirect effects simultaneously while removing measurement error from the variables of interest. Findings indicated that positive TSRQ and PTRQ influenced achievement via improved student engagement. Furthermore, a meta-analysis including 92 peer-reviewed articles and over 129,000 students supported the TSRQ predicts achievement pathways, particularly for lower achieving students and students in higher grades (Roorda et al., 2011). Finally, using the same sample as the present paper, McCormick and O'Connor (2015) employed hierarchical linear modeling (HLM) to investigate within– and between–child effects of TSRQ on math and reading achievement across first, third, and fifth grade. The authors found a between–child effect of Teacher–Student Conflict and a within–child effect of Teacher–Student Closeness on reading achievement.

STUDENT ACHIEVEMENT PREDICTS TEACHER–STUDENT RELATIONSHIP QUALITY

Students with greater academic competence at school entry benefit from improved TSRQ. Employing growth curve modeling with a subsample of 878 children from the National Institute of Child Health and Human Development's study of early child care (NICHD SECC), Jerome, Hamre, and Pianta (2009) investigated background variables that predicted changes in Teacher–Student Closeness and Teacher–Student Conflict between kindergarten and sixth grades. Findings showed lower academic achievement at school entry was associated with higher ratings of conflict and higher academic achievement was associated with more positive ratings of Teacher–Student Closeness, supporting the achievement to relationship hypothesis. Both measures of TSRQ were stable over time and neither were associated with measures of mother–child attachment, maternal education, nor maternal sensitivity. Achievement predicting teacher–student relationships is also supported by direct-observation research showing teacher preference for higher-achieving students (Brophy & Good, 1970). Brophy and Good provided a behavioral mechanism for this directionality by measuring teacher–student interactions in classrooms. Collecting direct-observation data in four first-grade classrooms grouped for academic ability, the researchers asked teachers to rate the most and least academically able students early in the academic year. Despite the restricted range due to reduced academic variability resulting from pre-existing achievement grouping, the researchers observed that students rated by teachers as more competent received significantly more praise, less criticism, more

[1] While TSRQ is also frequently expressed as STRQ in published work, all relational data collected were from teachers. Consequently, the measured construct is represented as TSRQ for the remainder of this paper.

opportunities to respond, more time to respond to questions, and more rephrased questions when initial answers were incorrect. Thus, it is reasonable to infer that the more positive interactions between teachers and students considered more academically capable could improve student engagement through both relational (positive teacher interaction) and instructional (improved query practice) mechanisms. Additionally, Murray and Murray (2004) investigated TSRQ as an outcome measure in a study using a diverse sample of 127 youths from disadvantaged backgrounds. The authors found variables highly correlated with achievement (behavioral and academic orientation) predicted TSRQ in data obtained later in the same school year. Put simply, it may be easier for teachers to build relationships with students that they perceive to be academically competent.

TEACHER–STUDENT RELATIONSHIP QUALITY AND STUDENT ACHIEVEMENT EXERT RECIPROCAL EFFECTS

As both directional pathways boast significant theoretical and conceptual support, it is also possible that reciprocal effects are present for achievement and relational constructs. Hughes, Luo, Kwok, and Loyd (2008) tested reciprocal pathways (i.e., cross-lagged direct effects) between three constructs (i.e., achievement, effortful engagement, and TSRQ) using three waves of panel data in a sample of 671 below–median achievers. Results provided strong support for longitudinal mediation in which more positive TSRQ predicted improved achievement via improved engagement. Reading and math achievement also had direct effects on TSRQ, particularly for low achievers. The authors posited that academic disengagement associated with learned helplessness (Diener & Dweck, 1978) may result from early academic failure and contribute to the achievement predicting TSRQ pathways indirectly via reduced student engagement.

RATIONALE AND PURPOSE

Selecting the most accurate statistical model is an important task, as the point of focus for teacher training is different if the predictive associations differ. If predicted changes in student achievement were driven exclusively by TSRQ, then low–performing schools should spend significant time and training resources in building better relational skills and practices within their teaching faculty. Furthermore, if the two principal components of TSRQ (Teacher–Student Closeness and Teacher–Student Conflict) were found to be differentially predictive, then efforts at school improvement would likely require even more specific training for staff. Conversely, if pre-existing levels of academic achievement were to serve as the central predictors of TSRQ, then school improvement efforts would likely require focused work on teacher attitudes and beliefs about struggling students to ensure those students benefit from a warm and supportive school experience as they meet academic challenges. Finally, if reciprocal relations were supported, then intervention would likely require some combination of both practices depending on school and teacher needs.

Student achievement, particularly at school entry, and measures of TSRQ are highly correlated. Consequently, the large and often contradictory body of methodologically sophisticated work on the relationship between TSRQ and achievement is by necessity bound to the population of selection and the assumptions of the analyses conducted. In a study that investigated the relationship between achievement and TSRQ using the same longitudinal sample as the current study (McCormick & O'Connor, 2015), HLM was employed to assess if TSRQ predicted achievement. However, the alternative possibilities that achievement drove changes in TSRQ over time or that reciprocal associations were present could not be assessed within the parameters of their study. In the present study, we use a longitudinal confirmatory factor analysis model of panel data across three elementary grades to investigate the relations among latent constructs of Teacher–Student Conflict, Teacher–Student Closeness, and measured student academic achievement in a multisite sample that reflects the broader student population. Latent variables were used to represent TSRQ in the current study. Latent variables represent the underlying construct that influences performance on individual, manifest items such that an increase in latent TSRQ will produce an increase in item scores. Second, using latent variables allows only what is common among the items to be represented as TSRQ (closeness or conflict), whereas specific and random variance (measurement error) is removed from the construct. Last, the use of latent variables allowed us to explicitly test factorial invariance, rather than assume, and potentially test differences in factor variances and latent means across time. Therefore, we first tested the assumption of consistent measurement of TSRQ across time. Furthermore, given longitudinal factorial invariance, we test heterogeneity of the factor variances and observed variances and equality of the latent means and observed means across time. We also test for the stability of the constructs across time (i.e., are the paths between two adjacent time points of the same construct the same across time) in addition to equivalent cross-lagged effects across time (controlling for previous within-time levels, do constructs predict changes in other constructs similarly across time). As reciprocal pathways of TSRQ and achievement have been found in published research using higher-risk samples, it was predicted that reciprocal pathways between measured reading and math achievement and teacher-reported conflict and closeness would be found.

METHOD

The study used data from the National Institute on Child Health and Human Development Study of Early Child Care and Youth Development (NICHD SECCYD). The NICHD SECCYD was a comprehensive longitudinal study that followed children from ages one month to 15 years

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($N = 1{,}364$). This study began in 1991 as a longitudinal design and was conducted in 10 different locations: Little Rock, AR; Irvine, CA; Lawrence, KS; Boston, MA; Philadelphia, PA; Pittsburgh, PA; Charlottesville, VA; Morganton, NC; Seattle, WA; Madison, WI. In order to be eligible to participate in this study, the mother had to be at least 18 years of age, understand and speak English, and be in generally good health. The study began with participants completing a home interview when the child was one month of age.

Participants

The study sample was drawn from the first three phases of the NICHD SECCYD. Data from these phases were collected from birth to fifth grade, and the current study analyzed first, third, and fifth grade data ($N = 1{,}133$) from the overall dataset. The sample demographic information was collected 1 month after birth and is as follows: 51.7% male, 48.3% female; 80.4% European American, 12.9% African American, 1.6% Asian or Pacific Islander, 0.4% American Indian, 6.1% Hispanic, and 4.7% Other. The ethnicity percentages exceeded 100% due to participants selecting multiple ethnic categories. Mothers' average level of education was 14.4 years. This variable was selected as a proxy for SES and was mean-centered for subsequent analyses.

INSTRUMENTS

The measures of TSRQ used in the NICHD SECCYD were the15-item Closeness and Conflict subscales from the Student-Teacher Relationship Scale (STRS; Pianta, 1992). The STRS collects teacher-reported information on both conflict and closeness in student–teacher relationships. While the total scale has been used as a manifest variable in studies of TSRQ (O'Connor & McCartney, 2007), this study used the observed responses as indicators of underlying latent variables, Conflict and Closeness, for two main reasons. First, investigations of the TSRQ have demonstrated strong discriminant validity between the two constructs. Studies using United States (Murray & Murray, 2004) and Norwegian samples (Drugli, 2013) have provided further support for conflict and closeness as separate and distinct. Second, the two constructs have demonstrated differential stability over time, with teacher-rated conflict evidencing greater stability than teacher-rated closeness (Gest et al., 2005). For each of the variables at first, third, and fifth grades used in the longitudinal analyses, descriptive statistics are reported in Table 1.

Teacher–Student Closeness

Teacher–Student Closeness was measured using the eight items (e.g., "Child openly shares feelings and experiences with me") from the Teacher Closeness subscale of the STRS (Pianta, 1992). The STRS is a teacher-report measure with items rated on a five-point, Likert-type scale (1 = d*efinitely does not apply* to 5 = *definitely applies*). The STRS Closeness scores exhibited high levels of internal consistency with Cronbach's $\alpha = .85$.

Teacher–Student Conflict

Teacher–Student Conflict was measured using the seven items from the Teacher Conflict subscale of the STRS (Pianta, 1992). Using the same five-point Likert-type format as the Closeness subscale, teachers rate items designed to measure conflictual relationships with specific students (e.g., "This child and I always seem to be struggling with each other"). The STRS conflict scores exhibited high levels of internal consistency with Cronbach's $\alpha = .90$ to .91.

Academic Achievement

Student academic achievement was measured with one reading and one math subtest from the Woodcock-Johnson Revised Tests of Achievement (WJ-R ACH; Woodcock & Johnson, 1989). Reading was measured with the Letter-Word Identification subtest. The first five items measure the participant's ability to match a pictographic representation of a word with an actual picture of the object, while the remaining items measure the participant's reading identification skills in identifying isolated letters and words. Internal reliability estimates for the sample scores were high within each grade ($\alpha = .88$–.92).

The Applied Problems subtest requires participants to analyze and solve practical math problems, recognize the procedure to be used, and perform relatively simple calculations. Internal reliability estimates for the sample scores were high within each grade ($\alpha = .81$–.83). Performance on the Letter-Word Identification and Applied Problems subtests were recorded using *W* scores, which are Rasch-based scores with equal interval units. A *W* score of 500, for example, indicates the average score (50th percentile) for a male student 10 years of age.

ANALYTIC STEPS

A measurement model was created to represent the teacher ratings across first, third, and fifth grade. The latent constructs under investigation in this study included: Teacher–Student Closeness and Teacher–Student Conflict. Observed scores were used to represent Reading and Math achievement as separate student achievement variables. Both Conflict and Closeness were measured with seven and eight indicators, respectively, at each grade (first, third, and fifth). A confirmatory factor analysis was performed on the individual constructs to ensure acceptable model fit and that each item loaded on its respective construct.

Longitudinal Factorial Invariance

We first tested the consistent measurement of the variables across grade levels (Little, 1997; Meredith, 1993). First, the configural invariance model, which served as our baseline model, tested whether the same pattern of free factor loadings

Table 1. Item Descriptives for Teacher–Student Relationship Quality and Math and Reading Achievement

Items	First Grade				Third Grade				Fifth Grade			
	Mean	*SD*	Skewness	Kurtosis	Mean	*SD*	Skewness	Kurtosis	Mean	*SD*	Skewness	Kurtosis
Conflict												
Struggle	1.62	1.00	1.71	2.01	1.65	1.04	1.58	1.35	1.61	0.99	1.68	1.80
Angry	1.57	0.92	1.89	3.14	1.64	1.00	1.72	2.17	1.66	1.00	1.60	1.64
Resistant	1.66	1.05	1.62	1.64	1.80	1.16	1.42	0.82	1.86	1.17	1.32	0.58
Drains	1.63	1.08	1.68	1.60	1.74	1.19	1.44	0.66	1.61	1.10	1.75	1.78
Bad Mood	1.51	0.90	2.07	3.91	1.65	1.07	1.67	1.89	1.57	0.98	1.83	2.64
Unpredict	1.42	0.83	2.45	6.16	1.51	0.95	2.03	3.29	1.52	0.93	2.03	3.48
Sneaky	1.51	0.97	1.99	2.91	1.64	1.07	1.61	1.28	1.60	1.05	1.76	2.03
Closeness												
Warm	4.43	0.79	–1.58	2.63	4.39	0.80	–1.32	1.39	4.21	0.87	–1.13	1.14
Affection	4.12	1.08	–1.20	0.63	4.03	1.05	–1.01	0.45	3.91	0.97	–0.57	–0.16
Comfort	4.09	0.92	–1.08	0.88	3.81	0.96	–0.76	0.05	3.50	1.02	–0.55	–0.33
Value	4.38	0.79	–1.02	0.24	4.27	0.83	–0.72	–0.61	4.16	0.86	–0.64	–0.43
Praise	4.71	0.59	–2.63	9.05	4.61	0.68	–2.04	4.40	4.56	0.67	–1.84	4.12
Shares	4.28	0.95	–1.50	1.74	4.15	1.02	–1.32	1.04	3.92	1.14	–0.91	–0.31
Tune	3.84	1.04	–0.78	–0.18	3.82	1.03	–0.78	–0.17	3.80	1.00	–0.73	–0.23
Open	4.09	1.03	–1.34	1.37	4.01	1.02	–1.16	0.80	3.80	1.09	–0.87	–0.08
Achievement												
Math	470.05	15.54	–0.04	–0.07	497.33	13.19	–1.54	5.60	509.82	12.85	–1.30	5.39
Reading	452.59	23.99	–0.09	0.21	493.86	18.73	–1.01	2.59	510.12	17.52	–0.96	3.43

Note. Struggle = My student and I always struggling with each other. Angry = My student easily becomes angry at me. Resistant = Student is angry/resistant after being disciplined. Drains = Dealing with my student drains my energy. Bad Mood = Student wakes up in bad mood, difficult day. Unpredict = Student's feelings to me can be unpredictable. Sneaky = My student is sneaky/manipulative with me. Warm = I share affectionate/warm relationship with my student. Affection = Student is uncomfortable with physical affection (reflected). Comfort = If upset, my student seeks comfort from me. Value = My student values his/her relationship with me. Praise = I praise student, he/she beams with pride. Shares = Student spontaneously shares personal information. Tune = It is easy to be in tune with what my student is feeling. Open = Student openly shares feelings/experience with me.

is the same across time. Next, we tested weak invariance or whether corresponding factor loadings are proportionally the same across time when the factor variances are allowed to vary across time. For example, this tests whether the same one-unit increase in Teacher–Student Conflict results in a similar unit increase on a specific conflict item consistently across time. Last, we tested strong invariance or whether corresponding intercepts are equal when the latent means are allowed to vary across time. If strong invariance is tenable then mean differences are not due to changes in the items across time but in the factor means across time.

Longitudinal Structural Invariance

We tested the variances and means across grade levels. A test of equal factor variances was performed, or whether the constructs are equally differentiated across time. Next we tested equivalence of the latent means, or whether the average of the construct is constant across time. We also tested whether the observed variances and means were equal across time.

Panel Model

Following tests of longitudinal factorial and structural invariance, procedures outlined by Little, Preacher, Selig, and Card (2007) were followed for model analyses. A longitudinal panel model was constructed to address questions about directional patterns (i.e., autoregressive and cross-lagged direct effects) related to the hypotheses. Specifically, we employed latent variable SEM to investigate the pattern of direct relations between Teacher–Student Closeness, Student

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Achievement, and Teacher–Student Conflict across first, third, and fifth grade.

The first step in building the model consisted of fitting autoregressive paths and within-time correlations to the longitudinal panel data. The autoregressive paths represent the direct effect within constructs across time, whereas the within-time correlations account for simultaneous relationships between constructs. For example, the autoregressive paths for Teacher–Student Closeness were created by having Teacher–Student Closeness at Grade 5 regressed onto Teacher–Student Closeness at Grade 3, which was regressed on Teacher–Student Closeness at Grade 1. Autoregressive paths can be used to test if an individual's scores relative to others (i.e., rank ordering) is similar across time. Corresponding autoregressive parameters across time were then tested for statistical equivalence as a test of differential stability.

The next step consisted of adding cross-lagged paths (also known as reciprocal paths) to the longitudinal panel data. Cross-lagged paths are a test of delayed relationships between constructs across time while previous levels of each construct are controlled. If two cross-lagged paths were statistically significantly *different from zero* (e.g., Student Achievement at Grade 1 to Teacher–Student Conflict at Grade 3 and Student Achievement at Grade 3 to Teacher–Student Conflict at Grade 5) then corresponding regression paths were tested if they were statistically significantly *different from each other*.

The likelihood ratio test (χ^2) was used to assess model fit changes when constraints were placed on parameters of the regression pathways. An unconditional model (i.e., without a covariate) and a conditional model (i.e., with a covariate) were also tested for statistical significance. The covariate was a proxy for SES (maternal education) and it was included to control for mean differences in home environment. If the covariate was statistically significant, it was retained in the model as a direct effect on Teacher–Student Closeness, Student Achievement, and Teacher–Student Conflict at Grade 1 only.

Missing Data

Missing data in the longitudinal sample were approximately 12.7%. For the total longitudinal sample, approximately 59% (665 cases) were not missing any data on any item at any grade level. Though the missing at random (MAR) assumption could not be explicitly tested, all cases were included (incomplete or not) and estimated using full information maximum likelihood (FIML). FIML handles missing data by estimating the model parameters in the presence of missing data in which all information (with the inclusion of auxiliary variables) is used to inform the parameter's values and standard errors in order to provide less biased estimates that are more likely to approximate population parameters.

Model Fit

Several different model fit criteria were used to assess model fit and whether constraints on statistical parameters were warranted. The likelihood ratio test (χ^2) was used for assessing nested model comparisons with an alpha level at $p < .05$ indicative of a statistically significant change in model chi-square. The evaluation of global model fit was assessed by the Root Mean Square Error of Approximation (RMSEA; Steiger & Lind, 1980), the Comparative Fit Index (CFI; Bentler, 1990), and the Standardized Root Mean Square Residual (SRMR; Hu & Bentler, 1999). Acceptable criteria for model fit were values: RMSEA $\leq .06$, CFI $\geq .95$, and SRMR $< .08$ (Hu & Bentler, 1999). Since mean structures were included, a CFI value $\geq .90$ was considered acceptable (Little, 2013). Longitudinal factorial invariance of the measurement model was tested using a change in CFI (ΔCFI) $\leq .01$ as the criterion for evidence of measurement invariance (Cheung & Rensvold, 2002). Tests of statistical equivalence of the factor variances and means, and observed variances and means were performed using the likelihood ratio test, with statistical significance at $p \geq .05$ indicative of structural invariance. The magnitude of those standardized regression pathways that were statistically significantly different from zero were interpreted according to the following effect size criteria: greater than .05, small; greater than .10, moderate; and greater than .25, large (Keith, 2006). Tests of equivalence of the latent and observed regression pathways were tested using the likelihood ratio test. M*plus*, Version 7.0 was used for all panel model analyses (Muthén & Muthén, 1998–2012).

RESULTS

The items used as reflective indicators in the longitudinal CFA models have descriptive statistics along with the standardized loadings reported in Table 1. The skewness and kurtosis values were approximately within the absolute value ranges of 2 and 7, respectively. The use of maximum likelihood is robust to non normal data distributions within this range (Enders, 2010). For Closeness, the standardized factor loadings ranged from first grade (.38 to .71), third grade (.40 to .73), and fifth grade (.44 to .73) with the "*uncomfortable with physical affection*" item having the lowest factor loadings and the "*openly shares feelings*" item having the highest factor loadings. For Conflict, the standardized factor loadings ranged from first grade (.66 to .74), third grade (.70 to .82), and fifth grade (.69 to .80) with the "*sneaky or manipulative with me*" item having the lowest factor loadings and the "*feelings toward me unpredictable*" item having the highest factor loading

Longitudinal Factorial Invariance

A test of configural invariance indicated a similar pattern of free loadings on corresponding latent factors across time (see Configural, Table 2). Next, a test of weak invariance indicated that corresponding factor loadings were proportional across time (see Weak, Table 2). Last, a test of strong invariance indicated that changes in the item means across time were due to differences in the latent means across time (see Strong, Table 2).

Longitudinal Structural Invariance

A test of whether the variances were equally differentiated across time was performed in which all corresponding variances (except error variances) were constrained to be equal across grades. All corresponding factor variances and observed variances were not equal across grades (see Omnibus, Table 2). Because the factor variances were not equal across time phantom variables were used to standardize the factor variances for valid comparisons of the latent regression pathways in the panel model (Little, 2013). Constraints were released and individual tests of equal factor variances and observed variances across grades were performed. Teacher–Student Closeness factor variances were equal across all grades (see Closeness factor, Table 2). Teacher–Student Conflict factor variances were not equal across grades (see Conflict factor, Table 2). The factor variances for Teacher–Student Conflict increased from first to third grade but was equal from third to fifth grade. The variances for student math achievement were not equal across all grades (see Math achievement, Table 2). Similar to teacher–student conflict, the variance for student math achievement was different from first to third grade (decreased) but the same from third to fifth grade. The variances for student reading achievement were not equal across grades (see Reading achievement, Table 2). Student reading achievement became increasingly homogeneous over time.

In addition to tests of equal variances across grades, tests of equal means across grades were performed. All corresponding latent means and observed means were not equal across grades (see Omnibus, Table 2). Constraints were released and

Table 2. Model Fit Statistics for Tests of Longitudinal Invariance

Model Tested	χ^2	*df*	RMSEA			CFI	SRMR	$\Delta\chi^2$	Δdf	*p*	ΔCFI
			Estimate	L 90% CI	H 90% CI						
Null model	31,823.168	1,341	–	–	–	–	–	–	–	–	–
Measurement model											
Configural	3,282.17	1,119	.041	.040	.043	.929	.047	–	–	–	–
Weak[a]	3,367.55	1,145	.041	.040	.043	.927	.050	–	–	–	.002
Strong[b]	3,579.26	1,171	.043	.041	.044	.921	.052	–	–	–	.006
Structural variances											
Omnibus[c]	3,859.25	1,179	.045	.043	.046	.912	.063	279.99	8	<.001*	–
Reading achievement[c]	3,774.58	1,173	.044	.043	.046	.915	.057	195.32	2	<.001*	–
Math achievement[c]	3,672.24	1,173	.043	.042	.045	.918	.054	92.98	2	<.001*	–
Closeness factor[c]	3,585.22	1,173	.043	.041	.044	.921	.053	5.95	2	.051	–
Conflict factor[c]	3,608.49	1,173	.043	.041	.044	.920	.055	29.23	2	.001*	–
Structural means											
Omnibus[c]	6,708.56	1,179	.064	.063	.066	.819	.197	3,129.30	8	<.001*	–
Reading achievement[c]	6,133.39	1,173	.061	.060	.063	.837	.144	2,554.13	2	<.001*	–
Math achievement[c]	6,272.87	1,173	.062	.060	.063	.833	.126	2,693.60	2	<.001*	–
Closeness factor[c]	3,676.24	1,173	.043	.042	.045	.918	.055	96.98	2	<.001*	–
Conflict factor[c]	3,594.02	1,173	.043	.041	.044	.921	.052	14.76	2	.001*	–

Note. RMSEA = Root Mean Square Error of Approximation. CFI = Comparative Fit Index. SRMR = Standardized Root Mean Square Residual. Measurement invariance is based on change in CFI (ΔCFI ≤ .01). Structural invariance is based on likelihood ratio test ($\Delta\chi^2$), which is statistically significant at $p < .05$.

[a]Compared to configural invariant model. [b]Compared to the weak invariant model. [c]Compared to the strong invariant model.

*The *p*-values with an asterisk indicate statistically significant.

individual tests of equal latent means and observed means across grades were performed. Teacher–Student Closeness latent means were not equal across all grades (see Closeness factor, Table 2). The average level of Teacher–Student Closeness decreased over time. Teacher–Student Conflict latent means were not equal across grades (see Conflict factor, Table 2). Initially, the average level of Teacher–Student Conflict increased from first to third grade but was equal from third to fifth grade. The average level of student math achievement was not equal across grades, with the average level increasing over time (see Math achievement, Table 2). Similarly, the average level of student reading achievement was not equal across grades, with the average level increasing over time (see Reading achievement, Table 2).

Panel Model

An initial model was estimated in which all constructs and observed variables at Grade 1 were regressed onto a maternal education covariate. This initial model with the maternal education covariate was compared to the final measurement model. The covariate was statistically significant at $p<.05$, with positive associations with Teacher–Student Closeness, Math Achievement, and Reading Achievement, and negative associations with Teacher–student Conflict. The addition of autoregressive paths indicated acceptable model fit according to all model fit statistics except the CFI (.897; see Conditional, within-variable paths freed, Table 3). The autoregressive paths were all statistically significant at $p<.05$ and positive. Next, all corresponding autoregressive paths were constrained to be equal. These added constraints on corresponding autoregressive paths did not statistically significantly worsen model fit, indicating the more parsimonious model should be retained (see Conditional, within-variable paths equal, Table 3). Model fit was acceptable according to all fit statistics except the CFI (.897). A cross-lagged model with reciprocal relations among latent constructs and observed variables (e.g., Closeness to Math, Math to Closeness) was estimated. When compared to the model with a covariate with corresponding autoregressive paths constrained to be equal, the addition of cross-lagged paths statistically significantly improved model fit, (see Conditional, reciprocal paths freed, Table 3). Model fit was acceptable. Corresponding cross-lagged paths were then constrained to be equal and compared to the same model with corresponding cross-lagged paths freed. These added constraints on corresponding cross-lagged paths did not substantially worsen model fit (see Conditional, reciprocal paths equal, Table 3). Results from the final model with a maternal education covariate entered at Time 1 only did not differ from the model in which the covariate was entered at all three time points. Consequently, the more parsimonious model (Time 1 only) was retained (see Figure 1 for final model).

Conditional Model interpretation

In the final model with a maternal education covariate (Figure 1), later Teacher–Student Closeness was explained by earlier Student Math Achievement even after controlling for previous levels of Teacher–Student Closeness. Later Student Math Achievement, however, was not explained by earlier Teacher–Student Closeness. Additionally, later Teacher–Student Conflict was only explained by itself.

Table 3. Fit Statistics for Longitudinal Panel Model

Model Tested	χ^2	*Df*	RMSEA			CFI	SRMR	$\Delta\chi^2$	Δdf	*p*
			Estimate	L 90% CI	H 90% CI					
Unconditional (without covariate)										
Within-variable paths freed[a]	4,020.66	1,211	.045	.044	.047	.908	.067	–	–	–
Within-variable paths equal[b]	4,023.39	1,215	.045	.044	.047	.908	.067	2.72	4	.605
Reciprocal paths freed[c]	3,782.60	1,191	.044	.042	.045	.915	.060	240.79	24	<.001*
Reciprocal paths equal[d]	3,801.82	1,203	.044	.042	.045	.915	.061	19.22	12	.083
Conditional (with covariate)										
Within-variable paths freed	4,575.49	1,446	.044	.042	.045	.897	.066	–	–	–
Within-variable paths equal[e]	4,577.70	1,450	.044	.042	.045	.897	.066	2.21	4	.697
Reciprocal paths freed[f]	4,333.73	1,426	.042	.041	.044	.905	.059	243.97	24	<.001*
Reciprocal paths equal[g]	4,349.65	1,438	.042	.041	.044	.904	.060	15.91	12	.195

Note. RMSEA = Root Mean Square Error of Approximation. CFI = Comparative Fit Index. SRMR = Standardized Root Mean Square Residual. [a]Compared to strong invariant model. [b]Compared to within-variable paths freed model. [c]Compared to within-variable paths equal model. [d]Compared to unconditional reciprocal paths freed model. [e]Compared to conditional within-variable paths freed model. [f]Compared to conditional within-variable paths equal model. [g]Compared to conditional reciprocal paths freed model.
*The *p*-values with an asterisk indicate statistically significant.

Teacher–Student Conflict did, however, explain individual differences in later Student Math Achievement after controlling for previous levels of Student Math Achievement. Not surprisingly, Student Math Achievement and Student Reading Achievement were reciprocal, indicating that after controlling for previous levels of each achievement variable, reading explained differences in mathematics and vice versa.

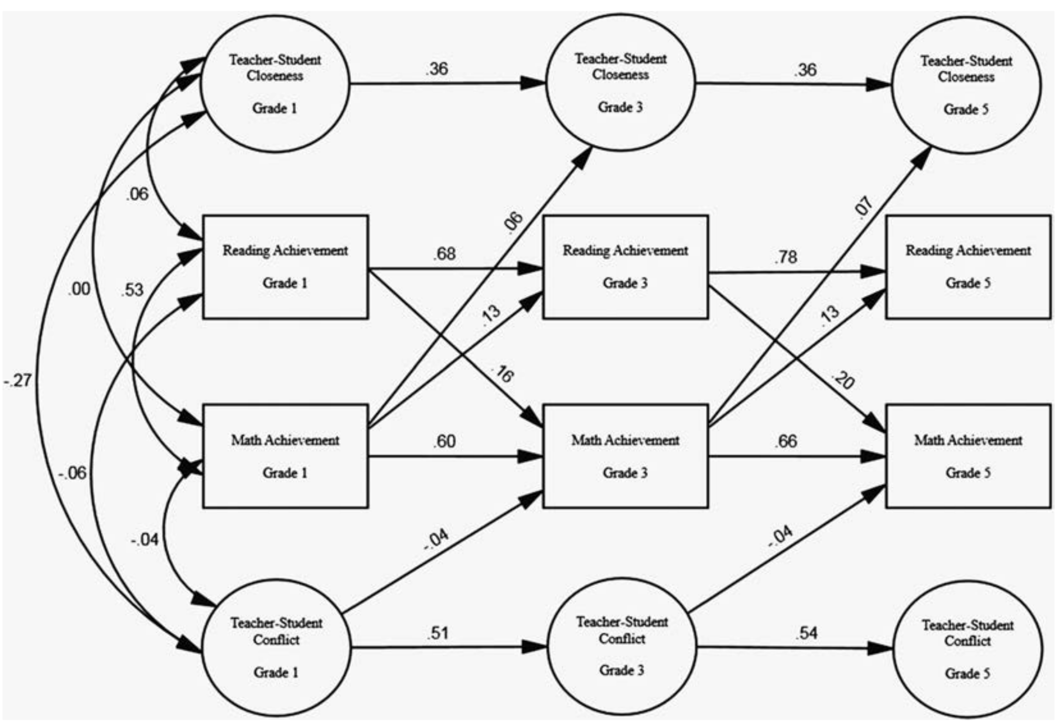
The within-time correlations between TSRQ and reading and math achievement were among the variables at Time 1, whereas the within-time correlations at Time 2 and Time 3 were among the residuals. Teacher–Student Conflict and Reading Achievement had a negative within-time correlation at third grade ($r = -.08$), whereas Teacher–Student Conflict and Math Achievement had a negative within-time correlation at fifth grade ($r = -.08$). However, Teacher–Student Conflict and Closeness had a consistent, negative within-time correlation that increased over time (r's = −.27 to −.42). Last, Reading Achievement and Math Achievement had a consistent positive within-time correlation that decreased over time (r's = .15 to .53).

Student Math Achievement had small effects ($\beta = .06$ to .07) on later Teacher–Student Closeness across grades after controlling for previous levels of Teacher–Student Closeness. For example, for each standard deviation increase in Student Math Achievement in first grade, it resulted in approximately a .06 standard deviation increase in Teacher–Student Closeness at third grade, even after controlling for previous Teacher–Student Closeness. However, although earlier Teacher–Student Conflict had statistically significant effects on later Student Math Achievement ($\beta = -.04$) across grades, the magnitude of these effects were not practically significant. Student Math Achievement had medium effects ($\beta = .13$) on later Student Reading Achievement as did Student Reading Achievement on later Student Math Achievement ($\beta = .16$ to .20). All corresponding cross-lagged pathways were equivalent across grades. The corresponding autoregressive paths for Teacher–Student Conflict ($\beta = .51$ to .54), Student Math Achievement ($\beta = .60$ to .66), and Student Reading Achievement ($\beta = .68$ to .78) were large and equivalent indicating stability across grades. For example, those with relatively higher Teacher–Student Conflict in first grade were also more likely to have higher Teacher–Student Conflict in fifth grade. Teacher–Student Closeness ($\beta = .36$ at both time points), however, was relatively less stable, indicating that those with relatively higher Teacher–Student Closeness at first grade may change to relatively lower closeness, or vice versa, from third to fifth grade. That is, the rank-ordering of individuals is likely to change over time.

DISCUSSION

The present study evaluated the longitudinal reciprocal relations between Teacher–Student Closeness, Teacher–Student Conflict, and measured reading and math

Figure 1. Final Conditional Cross-Lagged Longitudinal Panel Model



Note. Final longitudinal model includes regression pathways and Time 1 within-time correlations. All regression pathways, and TSRQ Closeness and Conflict, and Math and Reading Achievement Time 1 within-time correlations were statistically significant at p < .05. The indicators, covariate (maternal education), residuals, and remaining within-time correlations have been omitted from the diagram.

achievement in a large, multisite sample of youth across first, third, and fifth grades. Before addressing our main research question, we first tested factorial invariance across time. The establishment of strong invariance in the measurement model allowed us to test differences in the factor variances and latent means across time. Last, regression pathways in the structural model were examined. In the final model, math achievement predicted later changes in both Teacher–Student Closeness and reading achievement at both time points but not in Teacher–Student Conflict at any time point. Teacher–Student Conflict predicted longitudinal changes in later math achievement across all time points but Teacher–Student Closeness did not predict later math or reading achievement at any time point.

While these findings may seem surprising upon first inspection, decisions related to construct measurement offer guidance in reconciling unexpected results. The achievement variables were measured using a standardized achievement battery rather than classroom grades or teacher appraisals of students' academic competence. Use of standardized assessments has historically resulted in weaker TSRQ and achievement relations (Roorda et al., 2011) and have even been shown to result in entirely different results when compared directly. As an example, Maldonado-Carreño and Votruba-Drzal (2011) found that TSRQ only predicted achievement when teachers' ratings of academic competence were employed as the outcome variable and this result disappeared when a composite measure of standardized achievement was used. By selecting a standardized assessment, we pursued results that better approximated actual student learning with the implicit understanding that grades serve as a measure of success that are softer, statistically speaking, but no less meaningful.

Furthermore, the stability of the constructs served to drive much of our obtained results. Teacher–Student Closeness was much less stable than Teacher–Student Conflict. This is a common finding, as conflict has been conceptualized as more of student-level variable and closeness a dyad-specific feature of the relationship and thus more likely to change from classroom to classroom across years. The stability of the relational constructs is likely a meaningful contributor to these findings as Teacher–Student Closeness was much more likely to differ year to year, reducing its potential to predict measured achievement. Conversely, if Teacher–Student Conflict functions more as a student-level trait similar to temperament, then it is less likely to be modified by other measured variables. The achievement variables followed a similar pattern in that reading achievement was more stable, and therefore less likely to be impacted by relational variables. By fifth grade, maternal education, prior reading achievement, and prior math achievement explained almost all of the variance in student reading outcomes. Math achievement, however, was less stable over time and demonstrated some sensitivity to the relational construct of Teacher–Student Conflict. As conflict may both impact student engagement as well as time lost in instruction due to disciplinary infractions, the continuous practice and acquisition of new skills required by mathematics as a subject may well explain this longitudinal relation.

That said, while reading achievement at Grade 1 and Grade 3 predicted reading and math achievement at Grade 3 and Grade 5, respectively, there were no statistically significant pathways from reading achievement to closeness or conflict at any subsequent time point. However, reading achievement and Teacher–Student Conflict had a negative within-time correlation ($r = -.08$) at third grade, which may suggest a possible relation. For example, it may be that current conflictual relationships and reading achievement are related, but it is not a longitudinal process. Conversely, prior math achievement predicted subsequent math and reading achievement and subsequent Closeness at each measured time point. Prior Teacher–Student Conflict predicted subsequent math achievement, suggesting a statistically but practically insignificant longitudinal relation over time. Additionally, there was a negative within-time correlation ($r = -.08$) at fifth grade, suggesting that current increased teacher–student conflict was associated with lower math achievement or vice versa.

Improved validity in the findings is a result of two design strengths. First, the cross-lagged panel design allows for investigation of reciprocal associations between measured variables without specifying the predictors and outcomes in advance. This is particularly advantageous when theoretical and empirical work supports key variables functioning in either role and likely explains the significant differences between the present study and McCormick and O'Connor's (2015) study despite the same sample and measures. Their use of HLM was both sophisticated and thoughtfully conducted, but by methodological necessity, implied directional pathways. Conversely, the use of the panel model allowed for the variance to "fall as it may" once prior levels of the variables of interest were controlled. This is particularly important when the variables of interest have demonstrated reciprocal or unidirectional effects (in either direction) across similar and different samples as is the case with TSRQ and student achievement (Hughes & Kwok, 2007; Roorda et al., 2011).

Second, the large sample size within a longitudinal design across multiple sites strengthens confidence in obtained findings. Rather than explaining individual variability with results from the same teachers on different measures, data collected were obtained from different teachers on the same measure, reducing the impact of rater bias from specific teachers. Teacher–Student Closeness trended lower over time in general, and this may be related to actual changes in relationship quality. It is no doubt difficult to measure TSRQ in a manner that represents developmental changes in teacher–student relations while also maintaining consistency in data collection across longitudinal studies, and items that address Teacher–Student Closeness quite accurately in primary grades may lead to poorer model fit as students mature. In our estimation, the use of items that employ affection or comfort as measures of Teacher–Student Closeness is likely to result in model deterioration over time as overt displays of physical affection with teachers becomes less socially acceptable.

Measures sensitive to these developmentally appropriate transitions while holding true to the TSRQ construct warrant future study and refinement, particularly for diverse students with culturally different views of what defines acceptable expressions of closeness and conflict.

Implications

Two primary research implications may be gathered from the present study. First, that in a large, lower-risk sample, student achievement may well function as the principal longitudinal driver of TSRQ. Consequently, researchers should take care when employing analytic techniques that require predictive decisions to be made in advance (e.g., multiple regression, HLM). Second, combining achievement data into one single variable may result in lost information, as academic subjects with more structured, laddered curricula (math) may be more sensitive to relational quality than those subjects that grow in complexity but not necessarily in operation.

For school psychologists attempting to improve student outcomes, the implications are more nuanced. Implementing interventions or trainings aimed at improving teachers' relationships with students is a valuable endeavor, even if academic achievement benefits aren't likely to occur for the majority of students. However, the within-time correlations may serve to elucidate proximal periods of concern for students struggling with academic learning while also dealing with more conflictual relationships. Of note, Teacher–Student Conflict demonstrated a statistically significant within-time correlation with reading achievement at third grade, a period in which students transition from learning to read to independent learning from text. Similar effects were found for Teacher–Student Conflict and math achievement in fifth grade—at a time in which math complexity moves beyond simpler operations to more complex, multistep problems. School psychologists responsible for students at risk of failure may find benefit in monitoring relationship status during these periods of academic transition.

Limitations

The sample used in the current study primarily consisted of a low risk, European American sample, and this may have influenced the results. High-risk samples are typically used in longitudinal and cross-sectional studies of TSRQ, and it has been asserted within a comprehensive, meta-analytic review (Roorda et al., 2011) that higher-risk samples may benefit to a greater degree from supportive teachers and likewise, may suffer greater harm as a result of unsupportive and conflictual relationships with teachers. Given the increased stress levels experienced by children in higher-risk homes, it is reasonable that teacher effects may increase in high-risk samples due to teachers stepping in and providing support typically provided at home. If so, this would support Wentzel's (2002) contention that teaching practices that yield positive student outcomes are functionally similar to positive parenting practices. Additionally, the academic skills measured by the Applied Problems and Letter–Word Identification subtests differed in complexity and were collected as single subtests rather than multiple subtests representing a broad math achievement construct and broad reading achievement construct. There may be differences in measurement across groups when considering composite versus subtest achievement scores, and these differences may have influenced our findings. It is possible that had a composite measure of reading been collected that matched the cognitive complexity of the Applied Problems subtest, model results may have been impacted. Additionally, data were not available to include second and fourth grade within the analysis, and it is possible that inclusion of these grades would have impacted study results. Results should be viewed accordingly and not referenced as evidence that teachers are unimportant agents of student change. Rather, this longitudinal study adds to the literature base as a rarely conducted test of directionality in a sample with a broad range of ability, home and school advantage, and across multiple geographic locations. Studies using high-risk samples for TSRQ investigation often use intact student populations in schools and/or districts with a large percentage of at-risk students whereas the students represented within the current study attended a broad range of schools at multiple sites. Comparison of lower-achieving students to higher-achieving peers may have resulted in more negative teacher appraisals for the lower performing group and negatively impact subsequent interactions than might otherwise occur in higher-risk settings with a more homogenous, lower achieving classroom milieu.

Future Research

Future research should focus on four main areas of inquiry. First, evidence of factorial invariance across developmental stages is needed to maintain construct comparability across time as students mature—a threat to internal validity. If constructs are to be assessed in rating-scale format, then measurement should be carefully assessed across samples and ages to strengthen conclusion validity. Second, investigating just how modifiable teacher attitudes in this case are would serve to inform future intervention efforts. It is possible that as teachers are drawn from a pool of individuals with a history of positive academic expectancies, closer relationships may result from perceived similarities with high achievers. Thus, training and supervision in more inclusive relational practices may help to buffer a natural tendency to prefer higher-achieving students. Third, given the increasing Hispanic population in the United States, replication studies (see Lykken, 1968 for importance of constructive replication) with Hispanic populations at high- or low-risk of poor outcomes should be considered. Few studies have used appreciable numbers of the fastest growing U.S. student population when asking critically important questions of TSRQ related to closeness, conflict, and the potential role of cultural mismatch in impacting TSRQ across schools. Finally, while we found only slight relationships between TSRQ and future achievement, we did not include any indicators of classroom instructional quality or structure. It is possible that teacher–student relational variables represent necessary but insufficient conditions for improved student learning and the full picture of teachers' impact on academic trajectories can only be captured through a closer inspection of factors related to both relational and instructional quality.

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