Application of Dyadic Data Analysis in Pediatric Psychology: Cystic Fibrosis Health-Related Quality of Life and Anxiety in Child–Caregiver Dyads

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Objective To demonstrate the use of the actor–partner interdependence model (APIM) of dyadic relationships in a sample of children with cystic fibrosis (CF) and their caregivers. **Methods** Multilevel modeling evaluated relations between health-related quality of life (HRQOL) and anxiety in 29 child–caregiver dyads. The following effects were evaluated: actor and partner, and the respondent (i.e., child or caregiver) × HRQOL interaction. **Results** This study demonstrated a practical application of the APIM. Significant actor effects were found (i.e., lower child HRQOL was associated with increased child anxiety, caregiver anxiety increased as caregiver perceptions of their child's HRQOL decreased), but not partner effects. The significant interaction indicated that the effects were different for children and caregivers. **Conclusions** The APIM has the potential to increase pediatric researchers' understanding of how social relationships and environments impact health outcomes. Future research should consider using dyadic data analysis when youth and caregiver data are available.

Key words anxiety; cystic fibrosis; quality of life; statistical applications.

Overview of Dyadic Data Analysis in the Context of Pediatric Research

A fundamental assumption in behavioral and social science statistical methods is that independent or uncorrelated observations occur among dependent variables. These methods assume that once variation attributed to independent variables is controlled, the dependent variables are independent and uncorrelated. However, when using scores from questionnaires completed by children and caregivers who are related, which is common in pediatric and clinical child research, each child is uniquely linked to their caregiver. As a result, the assumption of independence is violated because both members of the child–caregiver dyad are not independent individuals and their scores are likely to be correlated (Cook & Kenny, 2005; Kenny, 1996; Kenny, Kashy, & Cook, 2006).

Even small amounts of nonindependence can result in inaccurate test statistics and degrees of freedom for the test statistic, leading to inflated statistical significance. Cook and Kenny (2005) contend that whenever nonindependence occurs, the dyad, not the individual, should be the unit of analysis. Two people in a relationship, such as a child with a chronic illness and his/her caregiver, have the ability to and often influence one another's thoughts, behaviors, and emotions. For example, the health-related quality of life (HRQOL) of children with cystic fibrosis (CF) can potentially impact caregiver

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functioning (e.g., psychological adjustment). However, relationship-based dyadic data are largely ignored and are often treated as studies of individual people (Kenny et al., 2006). Studies in which the same dependent variable has been simultaneously measured for both a child and his/her caregiver, but results are analyzed or published separately ignore that an essential assumption of independence has been violated (Kenny, 2011). In addition, the drawbacks of analyzing data separately (e.g., using traditional multiple regression) versus using dyadic data analysis has been delineated in a recent commentary by Kenny (2011). This commentary posits the following: (a) splitting samples into two parts results in a reduction of power (in fact, separate regression models would then only contain half the sample size) resulting in the potential to miss important results; (b) differing results may occur in each group which invites interpretations of differences when there are none; and (c) failing to measure the correspondence in the responses of the two dyad members occurs. Despite these arguments, confusion remains about the benefits of the APIM over traditional regression.

To address these analytic issues, Cook and Kenny (2005) developed dyadic data analysis with one approach being the actor–partner interdependence model (APIM), which investigates the processes that occur within dyads (as opposed to treating dyads as independent cases or averaging scores of dyad members). Notably, the APIM has a unique advantage over other analytic strategies involving dyadic data because it allows for the evaluation of variation within and between dyads (van Dulmen & Goncy, 2010). The primary components of the APIM are the actor and partner effects, which are comparable to the main effects in analysis of variance. The actor effect measures the degree to which a person's own characteristics impact his/her own outcomes; however, to be measured accurately, they need to be estimated while controlling for partner effects. Partner effects measure the degree to which one person is influenced by the other person or the partner (i.e., the effect of the partner's characteristics on the other person's outcome) and allow for the identification of relational phenomena. Notably, the correlations between the independent variables and the correlations between the residual variables allow for estimation of actor effects while controlling for partner effects, and estimation of partner effects while controlling for actor effects. Another important aspect of the APIM is the interactional model, in which one of the independent variables affects the size of the effect of the other independent variable on the dependent variable. In the APIM, partner effects that moderate the actor characteristics are of interest (i.e., actor–partner interactions) because these interactions can be important indicators of child outcomes especially in child–caregiver relationships. The interaction allows for the determination of differences in variables. In addition, other moderator variables such as age and sex can be tested in the APIM (Kenny et al., 2006).

Use of the APIM in Clinical-Health Studies Involving Children and Adults

The APIM has historically been applied to the evaluation of social relationships (e.g., the impact of depression on marital satisfaction in husbands and wives; Kouros, Papp, & Cummings, 2008), but recently, there has been an increasing number of health studies using the APIM with adult samples (Badr & Taylor, 2008; Franks, Wendorf, Gonzalez, & Ketterer, 2004; Mellon et al., 2009). Examples include evaluation of the impact of depression and stress in participants with early-stage breast cancer and their partners on physical health and well-being (Dorros, Card, Segrin, & Badger, 2010), effects of depression and anxiety on HRQOL in patients with heart failure and their spouses (Chung et al., 2009), and effects of relationship maintenance strategies on psychological distress and adjustment in couples coping with lung cancer (Badr & Taylor, 2008). Ackerman and colleagues (2010) argued that using dyadic models in health research has the potential to elucidate the field's understanding of the relation between physical health and the social environment.

Understanding physical health in the context of the pediatric social environment is also important. Despite the use of the APIM by health researchers, we are not aware of any studies in pediatrics or pediatric psychology that have used the APIM to evaluate child health in the context of the caregiver–child relationship. However, Hilliard and colleagues recently used structural equation modeling to account for nonindependence in their study of paternal involvement in adherence and glycemic control in children with type 1 diabetes (Hilliard et al., 2011). Pediatric research provides a plethora of opportunities for the application of dyadic data analysis using the APIM, especially because children with chronic conditions are almost always accompanied to medical appointments by at least one parent, usually the mother. In the pediatric clinical research setting, each member of the child–caregiver dyad has the potential to provide data on their own experiences (e.g., anxiety, HRQOL, adherence). In addition, caregivers typically provide proxy data regarding their child's experiences. Thus, dyadic data analysis is optimal when analyzing caregiver–child data.

Comparison of the APIM to Traditional Multiple Regression with a Pediatric Sample

Background Information

Consistent with Kenny's (2011) suggestion that research focused on families could benefit by evaluating the data in terms of dyads, the overall purpose of this article is to increase pediatric researchers' understanding of dyadic data analysis, and specifically the APIM, by illustrating its use in a sample of child–caregiver dyads in which the child has CF.

In the APIM illustration that follows, we used cross-sectional HRQOL and anxiety data from children with CF and their caregivers who had participated in a larger prospective study. Details of the larger study including methodology, informed consent procedures, and participation rates are described elsewhere (Modi et al., 2010). The overall purpose of the larger study was a multisite evaluation of changes in HRQOL of children and adolescents who were treated with intravenous antibiotics for a lung infection. The HRQOL of individuals with CF is impacted by lung infections, hospitalizations, and the complex and time-consuming treatment regimen including frequent clinic appointments. Therefore, we hypothesized that lower child and caregiver-proxy HRQOL would be associated with higher levels of their own anxiety (actor effects). It was also hypothesized that lower child HRQOL would be associated with higher caregiver anxiety, whereas lower caregiver-proxy HRQOL would be associated with higher child anxiety (partner effects). We explored the interaction of respondent with actor and partner HRQOL to determine whether the actor and partner effects were the same for children and caregivers. Twenty-nine dyads of children with CF ($M = 8.93$ years; $SD = 2.67$; ages 4.46–13.56 years) and their caregivers were used in this example. For ease of illustration, dyads were only included if there were child and caregiver HRQOL and anxiety data available. While there is no convenient program to estimate power, often power estimates are determined through simulation once good estimates of the parameters have been determined (Maas & Hox, 2005). Institutional review board approval was obtained as were caregiver consent and child assent.

Measures

For the purposes of this example, children and their caregivers completed the CF Questionnaire-Revised (CFQ-R; Modi & Quittner, 2003; Quittner, Buu, Messer, Modi, & Watrous, 2005), which uses a 4-point Likert scale and produces scaled scores ranging from 0 to 100, with higher scores representing better HRQOL. The CFQ-R Child Version consists of eight subscales: Physical (six items), Emotional (eight items), Social (seven items), Body Image (three items), Eating (three items), Treatment Burden (three items), Respiratory (four items), and Digestion (one item). Internal consistency coefficients for the CFQ-R Child Version have been found to be acceptable to excellent (Modi & Quittner, 2003; Quittner et al., 2005). Since the CFQ-R yields separate subscale scores and not a total score, for ease of illustration, a total CFQ-R score was created by adding the individual CFQ-R subscale scores and dividing by the total number of subscales. For this study, Cronbach's α for all 35 items of the CFQ-R Child Version was .82. Caregivers completed the caregiver/parent-proxy version of the CFQ-R, which consists of all child subscales (Physical, nine items; Emotional, five items; Body Image, three items; Eating, two items; Treatment Burden, three items; Respiratory, six items; and Digestion, three items) except Social, and four additional subscales (Vitality, five items; Health Perceptions, three items; School, three items; Weight, one item). Similar to the child CFQ-R, a CFQ-R Caregiver/Parent version total score was created by adding the individual CFQ-R subscale scores and dividing by the total number of subscales. Cronbach's α for all 44 items of the Caregiver/Parent version was .88.

To assess current or temporary levels of anxiety, the state anxiety subscales from the State-Trait Anxiety Inventory for Children (STAIC; Spielberger, Edwards, Montuori, & Lushene, 1970) and State-Trait Anxiety Inventory (STAI; Spielberger, 1970) were completed. Children-rated items on a 3-point Likert scale with Total scores ranging from 20 to 60 (higher scores indicated higher levels of anxiety). Coefficient α for state anxiety was .82 for children. Caregivers rated items on a 4-point Likert scale with Total scores ranging from 20 to 80 (higher scores also indicated higher levels of anxiety). Coefficient α for state anxiety was .93 for caregivers.

Lung functioning was assessed through spirometry using American Thoracic Society standards. Wang and Hankinson equations (Hankinson, Odencrantz, & Fedan, 1999; Wang, Dockery, Wypij, Fay, & Ferris, 1993) were used to calculate Forced Expiratory Volume in 1 s (FEV_1 % predicted). Lower values indicated poorer lung functioning.

Overview of Analytic Plan

As recommended by Kenny, Kashy, and Cook (2006), prior to completing any analyses, the data were structured pairwise (also known as the double-entry structure; see Figure 1). Thus, in our study of child–caregiver dyads,

ID	fev1	age	state_A	state_P	respondent_A	respondent_P	Overall_Avg_A	Overall_Avg_P	Zage	Zfev1	ZOverall_Avg_A	ZOverall_Avg_P	Zstate_A	Zstate_P
4	113.00	6.34	30.00	46.00	-1.00	1.00	67.81	73.10	-.96858	1.26594	.37188	.76867	-.43370	1.10834
4	113.00	6.34	46.00	30.00	1.00	-1.00	73.10	67.81	-.96858	1.26594	.76867	.37188	1.10834	-.43370
5	72.00	5.98	32.00	56.00	-1.00	1.00	49.90	49.49	-1.10340	-.76800	-.97123	-1.00167	-.24094	2.07212
5	72.00	5.98	56.00	32.00	1.00	-1.00	49.49	49.90	-1.10340	-.76800	-1.00167	-.97123	2.07212	-.24094
6	64.00	9.64	22.00	50.00	-1.00	1.00	71.45	70.81	.26733	-1.16487	.64534	.59694	-1.20472	1.49386
6	64.00	9.64	50.00	22.00	1.00	-1.00	70.81	71.45	.26733	-1.16487	.59694	.64534	1.49386	-1.20472

Figure 1. Example of raw data that is structured pairwise. *Note.* The supplementary full data file can be found at JPEPSY online.

the child's data were entered as one set of variables, and the caregiver's data were entered as the partner variable. For example, there were two variables: State_A (on the child's record, the child's state anxiety score) and State_P (on the child's record, the caregiver's state anxiety score).

Next, we illustrate use of the APIM through multilevel modeling in SPSS, which takes into account both members of the dyad. Consistent with Kenny and colleagues (2006), the child–caregiver dyads were treated as distinguishable because of their separate roles in the family. Following illustration of the APIM, we provide the traditional multiple regression results with models analyzed separately for children and caregivers to demonstrate the additional information provided by analyzing the dyadic data.

The APIM Specification and Results

The APIM regression model determined the impact of children's HRQOL and their caregivers' perceptions of children's HRQOL (i.e., caregiver-proxy) on their own anxiety as well as their partner's anxiety. Lung functioning and age were included as covariates in the analyses ($r = -0.03$, $p > .05$). The following variables were entered into the APIM: respondent (coded as $-1 =$ child, $+1 =$ caregiver), FEV_1 % predicted, child age, actor HRQOL and partner HRQOL (main effects) and two interactions—respondent × actor HRQOL and respondent × partner HRQOL. The interactions allowed us to determine if actor and partner effects were the same for children and caregivers. The dependent variables were child and caregiver anxiety. Syntax for this analysis is provided in Appendix A.

Table I demonstrates that after controlling for current lung functioning and age, actor effects were significant. These results suggest that child HRQOL and caregiver-proxy HRQOL are more likely a result of their own characteristics and/or perceptions of relationship functioning, rather than the other person's characteristics (i.e., the operative causal variable is the person's own score). In our example, lower child HRQOL was associated with increased child anxiety. In addition, caregiver anxiety increased as caregiver perceptions of their child's HRQOL decreased. Partner effects were not significant. The

Table I. *APIM Results for Child–Caregiver Dyads*

Dependent variable = Actor State Anxiety[a]		
APIM parameters	*B* (SE)	*p*
Respondent_A	−.06 (.12)	.64
FEV1_A	.13 (.13)	.32
Age_A	−.23 (.12)	.07
HRQOL_A	−.38 (.13)	.01
HRQOL_P	.09 (.13)	.48
Respondent_A × HRQOL_A	.07 (.13)	.59
Respondent_A × HRQOL_P	.27 (.13)	.04

Note. These are standardized beta coefficients. Data were analyzed with the pairwise dataset to account for the dyad.
[a]Although Actor State Anxiety was used as the dependent variable, the same results are obtained if Partner State Anxiety is used given that the data is structured pairwise.

interaction of respondent × actor HRQOL was not significant, whereas the interaction of respondent × partner HRQOL was significant. Child HRQOL impacted caregiver anxiety more than caregiver-proxy HRQOL impacted child anxiety.

Interpretation of Effects

Using the results from Table I, the following effects were calculated and are reflected in the paths contained in Figure 2:

1. actor effect for children = HRQOL_A + (Respondent_A × HRQOL_A)(-1); e.g., $-.45 = -.38 + (.07)(-1)$
2. actor effect for caregivers = HRQOL_A + (Respondent_A × HRQOL_A)($+1$)
3. partner effect for child to caregivers = HRQOL_P + (Respondent_P × HRQOL_P)($+1$); and
4. partner effect for caregiver to child = HRQOL_P + (Respondent_P × HRQOL_P)(-1).

Variance Explained and Effect Sizes

Pseudo R^2 was calculated to determine the estimate of variance explained by the predictors. Pseudo R^2 is defined as 1− (estimates of the variance and covariance from the

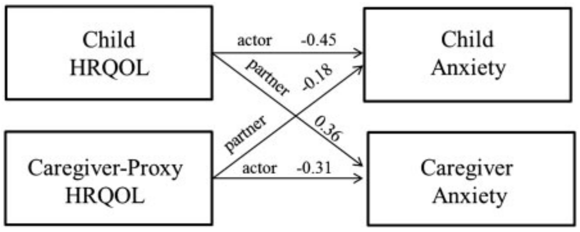

Figure 2. Illustration of relations between HRQOL and anxiety using APIM.

unrestricted model)/(estimates of the variance and covariance from the restricted model). For our model, Pseudo R^2 was 11.41% and the adjusted effect size was .26. Kenny and colleagues (2006) acknowledged the complexities of calculating effect sizes and power in multilevel modeling. Since the mathematics involved are beyond the scope of this illustration, we refer the reader to their text (pp. 179–180) for further explanation.

Traditional Multiple Regression Model Specification and Results

Table II contains separate regression results for children and caregivers. For children, after controlling for FEV_1 % predicted and age, child HRQOL significantly predicted child anxiety. For caregivers, after controlling for FEV_1 % predicted and age, child HRQOL significantly predicted caregiver anxiety.

Analytic Differences Between Models and Value Added Benefit of the APIM

Tables I and II reflecting the APIM and traditional multiple regression, respectively, highlight the drawbacks of analyzing data separately (Kenny, 2011). Most importantly, the interdependence of the dependent anxiety variables is not accounted for since it is impossible to include two dependent variables in the same traditional regression equation. Despite the small sample size, we found an actor effect using the APIM. Splitting the data into two samples reduced the sample size by half and resulted in a nonsignificant association between caregiver-proxy HRQOL and caregiver anxiety. Traditional multiple regression does not account for the dyad members. In the APIM, a variable was included in the analysis that reflected the dyadic nature of the data. Finally, although our data did not reveal a partner effect, it was possible to evaluate the potential partner effect using the APIM; it is impossible to do so in traditional multiple regression.

Table II. *Separate Regression Results for Children and Caregivers*

	Dependent variable = Child State Anxiety		
	B	SE	*p*
FEV_1 %	.04	.20	.83
Age	−.03	.18	.88
Caregiver HRQOL	−.11	.20	.60
Child HRQOL	−.46	.18	.02
	Dependent variable = Caregiver State Anxiety		
	B	SE	*p*
FEV_1 %	.21	.18	.25
Age	−.40	.17	.03
Caregiver-proxy HRQOL	−.37	.19	.06
Child HRQOL	.38	.17	.04

Discussion

The APIM is an innovative method for analyzing dyadic data while accounting for the nonindependent data. Traditionally, these data would have been analyzed in separate regression models with child outcome variables in one model and their caregiver outcome data in another. However, in contrast to the traditional regression analyses that we presented, the APIM allowed us to determine that the child's own HRQOL or the caregiver's perceptions of their child's HRQOL affected each person's own anxiety (actor effect) while controlling for the partner's influence. Partner main effects were not significant (i.e., the partner in these dyads was not influencing the other's outcomes), which will not always be the case in dyadic data. The overall goal of the current study was to describe dyadic data analysis and to illustrate use of the APIM in a pediatric sample. Although Kenny's (2011) commentary suggested several strategies for analyzing dyadic data, to our knowledge, this is the first study to provide an illustration of the APIM using actual data in a pediatric sample.

Future research using the APIM has the potential to elucidate pediatric health outcomes as they relate to the characteristics of their caregivers (i.e., mother, father) or even siblings (Ackerman, Ledermann, & Kenny, 2010). Exploration of dyadic data using the APIM will benefit the field of pediatric psychology by illuminating the relations between the social environment and disease progression and health-related behaviors (Ackerman et al., 2010) and applications exist for longitudinal research as well. In addition, the APIM is underused, but has significant implications for clinical-child researchers; our review of the extant literature revealed very few studies that applied the APIM in this area. For example, Pesonen and colleagues used the APIM to demonstrate whether a parent's depressive vulnerability was associated with their own and the

other parent's ratings of their child's temperament (Pesonen, Raikkonen, Heinonen, Jarvenpaa, & Strandberg, 2006). The APIM also has the potential to illuminate how multiple informants' perceptions and discrepancies are related to child and adolescent psychopathology (De Los Reyes, 2011) and cross-informant data (van Dulmen & Goncy, 2010).

The CF sample in this study illustrates the utility of the APIM in pediatrics and we hope that others will apply use of the APIM in their own research with children with chronic diseases and their family members. Although the sample was small and underpowered, which suggests the need for replication, we did find an actor effect and the interaction involving the respondent was significant. More generally, however, power and sample size are problematic issues and are an area of concern in multilevel modeling approaches (Maas & Hox, 2005; Snijders, 2005; Peugh, 2010), as are missing data (Stapleton & Thomas, 2008). Imputation is one way to handle missing data (Stapleton & Thomas, 2008). Perhaps with a larger sample size, we would have detected partner effects. Notably, because the overall purpose of this study was to illustrate the use of the APIM in a pediatric sample, the clinical findings should be interpreted within this context.

The application of the APIM has great potential in all areas of pediatric and clinical child psychology research. Given that caregivers play a fundamental role in many aspects of their children's development, whether or not a chronic illness is involved, the dyadic nature of the relationship is a rich area for exploration and growth. We believe future research using the APIM will provide valuable information about how children with chronic conditions and their caregivers influence each others' outcomes. Moreover, using an innovative technique such as the APIM has the potential to influence both the design of future studies and the clinical care of pediatric patients with chronic illness, particularly if initial studies demonstrate the importance of evaluating both the individual and the dyad.

Supplementary Data

Supplementary data can be found at: http://www.jpepsy.oxfordjournals.org/.

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References

Ackerman, R. A., Ledermann, T., & Kenny, D. A. (2010). Using dyadic analysis in health psychology. *The European Health Psychologist, 12*, 18–20.

Badr, H., & Taylor, C. L. (2008). Effects of relationship maintenance on psychological distress and dyadic adjustment among couples coping with lung cancer. *Health Psychology, 27*, 616–627.

Chung, M. L., Lennie, T. A., Riegel, B., Wu, J. R., Dekker, R. L., & Moser, D. K. (2009). Marital status as an independent predictor of event-free survival of patients with heart failure. *American Journal of Critical Care, 18*, 562–570.

Cook, W. L., & Kenny, D. A. (2005). The actor-partner interdependence model: A model of bidirectional effects in developmental studies. *International Journal of Behavioral Development, 29*, 101–109.

De Los Reyes, A. (2011). Introduction to the special section: More than measurement error: Discovering meaning behind informant discrepancies in clinical assessments of children and adolescents. *Journal of Clinical Child & Adolescent Psychology, 40*, 1–9.

Dorros, S. M., Card, N. A., Segrin, C., & Badger, T. A. (2010). Interdependence in women with breast cancer and their partners: an interindividual model of distress. *Journal of Consulting and Clinical Psychology, 78*, 121–125.

Franks, M. M., Wendorf, C. A., Gonzalez, R., & Ketterer, M. (2004). Aid and influence: Health-promoting exchanges of older married partners. *Journal of Social and Personal Relationships, 21*, 431–445.

Hankinson, J. L., Odencrantz, J. R., & Fedan, K. B. (1999). Spirometric reference values from a sample of the general U.S. population. *American Journal of Respiratory and Critical Care Medicine, 159*, 179–187.

Hilliard, M. E., Rohan, J. M., Carle, A. C., Pendley, J. S., Delamater, A., & Drotar, D. (2011). Fathers' involvement in preadolescents' diabetes adherence and glycemic control. *Journal of Pediatric Psychology, 36*, 911–922.

Kenny, D. A. (1996). Models of nonindependence in dyadic research. *Journal of Social and Personal Relationships, 13*, 279–294.

Kenny, D. A. (2011). Commentary: Dyadic analyses of family data. *Journal of Pediatric Psychology, 36*, 630–633.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *The analysis of dyadic data*. New York: Guilford Press.

Kouros, C. D., Papp, L. M., & Cummings, E. M. (2008). Interrelations and moderators of longitudinal links between marital satisfaction and depressive symptoms among couples in established relationships. *Journal of Family Psychology, 22*, 667–677.
Maas, C. J. M., & Hox, J. J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology, 1*, 86–92.
Mellon, S., Janisse, J., Gold, R., Cichon, M., Berry-Bobovski, L., Tainsky, M. A., & Simon, M. S. (2009). Predictors of decision making in families at risk for inherited breast/ovarian cancer. *Health Psychology, 28*, 38–47.
Modi, A. C., Lim, C. S., Driscoll, K. A., Piazza-Waggoner, C., Quittner, A. L., & Wooldridge, J. (2010). Changes in pediatric health-related quality of life in cystic fibrosis after IV antibiotic treatment for pulmonary exacerbations. *Journal of Clinical Psychology in Medical Settings, 17*, 49–55.
Modi, A. C., & Quittner, A. L. (2003). Validation of a disease-specific measure of health-related quality of life for children with cystic fibrosis. *Journal of Pediatric Psychology, 28*, 535–545.
Pesonen, A. K., Raikkonen, K., Heinonen, K., Jarvenpaa, A. L., & Strandberg, T. E. (2006). Depressive vulnerability in parents and their 5-year-old child's temperament: a family system perspective. *Journal of Family Psychology, 20*, 648–655.
Peugh, J. L. (2010). A practical guide to multilevel modeling. *Journal of School Psychology, 48*, 85–112.
Quittner, A. L., Buu, A., Messer, M. A., Modi, A. C., & Watrous, M. (2005). Development and validation of The Cystic Fibrosis Questionnaire in the United States: A health-related quality of life measure for cystic fibrosis. *Chest, 128*, 2347–2354.
Snijders, T. A. B. (2005). Power and sample size in multilevel linear models. In B. S. Everitt, & D. C. Howell (Eds.), *Encyclopedia of Statistics in Behavioral Science, Vol. 3*. Chicester: Wiley.
Spielberger, C. (1970). *State-Trait Anxiety Inventory for Adults*. Redwood City, CA: MindGarden, Inc.
Spielberger, C., Edwards, C., Montuori, J., & Lushene, R. (1970). *State-Trait Anxiety Inventory for Children*. Redwood City, CA: MindGarden, Inc.
Stapleton, L. M., & Thomas, S. L. (2008). The use of national databases for teaching and research. In A. O'Connell, & D. B. McCoach (Eds.), *Multilevel modeling of educational data*. Charlotte: Information Age Publishing Inc.
van Dulmen, M. H., & Goncy, E. A. (2010). Extending the actor-partner interdependence model to include cross-informant data. *Journal of Adolescence, 33*, 869–877.
Wang, X., Dockery, D. W., Wypij, D., Fay, M. E., & Ferris, B. G. Jr. (1993). Pulmonary function between 6 and 18 years of age. *Pediatric Pulmonology, 15*, 75–88.

Appendix A

Mixed

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Zstate_A WITH RESPONDENT_A Zfev1 Zage ZOverall_Avg_A ZOverall_Avg_P.
    /FIXED = RESPONDENT_A Zfev1 Zage ZOverall_Avg_A ZOverall_Avg_P.
    RESPONDENT_A*ZOverall_Avg_A RESPONDENT_A*ZOverall_Avg_P.
    /METHOD = REML.
    /PRINT = SOLUTION TESTCOV.
    /REPEATED = RESPONDENT_A | SUBJECT(ID) COVTYPE(CSH).
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Variable Label	Variable Explanation
Zstate_A*	Actor's state anxiety score
RESPONDENT_A	Respondent (either caregiver or child)
Zfev1	FEV% predicted represents lung functioning
Zage	Child's age
ZOverall_Avg_A	Actor's quality of life score
ZOverall_Avg_P	Partner's quality of life score
RESPONDENT_A*ZOverall_Avg_A	Actor respondent and Actor quality of life interaction
RESPONDENT_A*ZOverall_Avg_P	Actor respondent and Partner quality of life interaction

Note. *Z represents standardized variable.